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Currency Crises Early Warning Systems: why they should be Dynamic

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Abstract

This paper introduces a new generation of Early Warning Systems (EWS) which takes into account dynamics within a system composed by binary variables. We elaborate on Kauppi and Saikonnen (2008), which allows to consider several dynamic specifications and to use an exact maximum likelihood estimation method. Applied so as to predict currency crises for fifteen countries, this new EWS turns out to exhibit significantly better predictive abilities than the existing models both within and out of the sample.

Key words: dynamic models, currency crisis, Early Warning System.

J.E.L. Classification: C33, F37

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1 Introduction

The recent subprime crisis has renewed the interest for Early Warning Systems (EWS). In principle, they should be able to ring before the occurrence of a financial crisis letting enough time for authorities to implement adequate rescuing policies to prevent or at least to smooth the perverse effects of the turmoil. Unfortunately, the existing EWS have remained silent at the edge of the recent financial crisis, leading researchers to renew their models. [1] This paper follows this objective emphasizing the importance of crisis dynamics for the new generation of EWS.

At first sight, understanding why detecting a crisis appears so difficult is fastidious as forecasting techniques have substantially improved over the last decades. This difficulty actually lies in the specificity of EWS, that aim at accurately detecting the occurrence of a crisis, which is by essence a binary variable taking the value of one when the event occurs, and the value of zero otherwise. Hence, it is not possible to directly implement the methods proposed in times series econometrics such as vector autoregression. Thus, following Kaminski, Lizondo and Reinhart (1998) (hereafter KLR), the first EWS was elaborated upon a signalling approach. Using a large set of potentially informative variables [2], they identified a threshold beyond which a crisis is signaled. The properties of such an EWS clearly depend on this cut-off point. KLR estimated it as the threshold value that minimizes the ratio between the number of crises incorrectly and correctly detected, also called the noise-to-signal ratio. [3] Once the variable specific threshold is determined, it is possible to build an aggregate indicator as a weighted combination of the variables, where each weight corresponds to the inverse of the associated noise to signal ratio. Hence, the so built EWS should exhibit a positive trend as the occurrence of a crisis increases.

Berg and Patillo (1999) (hereafter BP) proposed to use a static panel probit model as an alternative to the signalling approach. Hence, the binary crisis variable is treated as endogenous and explained by a set of macroeconomic variables. Evaluation criteria, such as the quadratic probability score (QPS) and the log probability score (LPS), indicate that their EWS exhibit better forecasting abilities (within and out of the sample) than the KLR one. Several extensions have been proposed: Kumar et al., (2003) advocate the use of panel logit instead of panel probit. Fuertes and Kalotychou, (2007) and Berg et al., (2008) analyze the presence of country clusters and their consequences for the EWS. Bussiere and Fratzscher (2006) suppose that a post-crisis specific period may be present, and consider the crisis as a ternary variable instead of a binary one, thus developing a multinomial logit EWS (Bussiere

1. See Rose and Spiegel (2010)

2. KLR consider 15 variables characterizing the domestic macroeconomic conditions, the external position and the financial sector of the considered countries.

3. Alternative estimation methods are available. See Candelon et al. (2009) for a discussion of this point.

and Fratzscher, 2006). Moreover, as the estimation methods for panel limited dependent variables are quite standard and available in almost all econometric softwares, this type of EWS has been extensively implemented in applied studies.

Nevertheless, both previous EWS are static and assume that the probability to exit a crisis period depends only on a set of macroeconomic variables, representing the implemented economic policies. This assumption is not supported by most empirical studies which show that the longer a country is in a crisis period, the higher the probability to exit the crisis will be, whatever the political reaction (see Tudela, 2004). Besides, Berg and Coke (2004) showed that EWS are *per nature* autoregressive, as they should ring not only one period before the occurrence of a crisis but during j periods, where j is the forecast horizon. Hence, it appears difficult for a static model to reproduce such a property.

To overcome the absence of dynamics, another mainstream of the literature proposes EWS elaborated on Markov-switching models (MS hereafter) (Abiad, 2003; Martinez-Peria, 2002; Fratzcher, 2003). This type of EWS can take into consideration dynamic processes which are specific to the crisis or non-crisis regime. Nevertheless, as these models are shaped for continuous variables, they cannot be used in case of the crisis binary variable, without imposing another *ad hoc* threshold. Instead, they consider a market pressure index, which is a continuous indicator of the stress faced by a country's currency. Although this approach is *per se* interesting, it has been shown by Candelon et al. (2009) that its predicting abilities are lower compared to the BP EWS. Moreover, a panel version of MS model is, to the best of our knowledge, not available.

Therefore, our paper proposes a new generation of EWS which reconciles the limited dependent property of the crisis variable and the dynamic dimension of this phenomenon. Particular attention is given to the specification and the estimation of such models. Actually, the dynamics of crises can be apprehended in several ways. First, it can be included as a lagged binary crisis variable. Thus, the EWS to be estimated looks like an autoregressive (AR) binary model, where the lagged binary variable summarizes all the past information of the system. Second, dynamics can be introduced via the past probability of being in a crisis regime. Finally, the two previous specifications should allow for the presence of past macroeconomic variables representing the economic policies experienced by a certain country. Given all these different specifications, the estimation methodology proposed should be flexible enough to allow for specification tests. It is the recent paper of Kauppi and Saikonnen (2008) that proposes an exact Maximum Likelihood estimation fitted to all these model specifications. [4] Beyond being easy to program in most common econometric softwares [5] and not time intensive (results are obtained in a few second), this framework allows to detect

4. A previous attempt to estimate one specific dynamic specification has been proposed by Falcetti and Tudela (2006) using a smoothly simulated likelihood estimation.

5. All Matlab program are available from the authors upon request.

the best dynamic specification via the well-known information criteria. While Kauppi and Saikkonen (2008) consider exclusively a time series framework, we extend it to a fixed effects panel based EWS by elaborating on Carro (2007).

In an empirical analysis, we aim to build a currency crisis EWS for a sample of fifteen emerging countries. The predictive abilities (within and out of the sample) of this new EWS compared to a wide range of alternative EWS (in particular the MS and the static logit models) are then investigated using the unified evaluation framework proposed by Candelon et al. (2009). Anticipating on our results, it turns out that the dynamic model including the lagged binary dependent variable outperforms (in-sample and out-of sample) most of the other specifications. Moreover, it appears the the new EWS has incredibly good out-of-sample forecasting abilities when the forecast horizon increases. Considering a 24 month horizon, it identifies correctly almost all crisis and calm periods (more than 96% of the crisis periods and more than 98.2% of the calm ones) whatever the country and the type of analysis (time-series or panel). Finally, it turns out that the dynamic logit EWS outperforms its main competitors: the static logit and the MS.

This paper is structured as follows: the new estimation methods used for dynamic limited dependent EWS both in time-series and panel are presented in section 2. The database, the currency crisis dating methods as well as the estimation results are scrutinized in section 3. Section 4 proposes a comparison of the forecasting abilities of the models, while section 5 concludes.

2 A Dynamic Specification of EWS

In this section, the dynamic limited dependent EWS is presented both in its time-series and panel version. To date, almost all EWS models are static and do not exploit the persistence property of the crisis, captured by a lagged crisis index. This paper is the first one to consider a dynamic version of EWS based on an exact maximum likelihood estimation. Actually it was Kauppi and Saikkonen (2008) who showed that a maximum likelihood estimator (ML) can be implemented under appropriate regularity conditions (stationarity of explanatory variables and normality of the random variables), and it has desirable large sample properties. Moreover, within this framework it is possible to compare several dynamic alternatives: for example, Kauppi and Saikonnen (2008), show that a dynamic model including both the lagged value of the index and the one of the binary variable itself predicts U.S. recessions better than a static model.

2.1 Specification and Estimation

Let us consider first the time-series version of the dynamic limited dependent EWS. We denote by $y_{n,t}$, $t \in \{1, 2, ..., T\}$ the currency crisis binary variable for country n, taking the value of 1 if there will be at least a crisis in the following j months and 0 if not and by $x_{n,t}$ the matrix of explanatory variables, whose first column is a unit vector. For ease of computation, hereafter n will be omitted.

When using a logit model, the one-step-ahead dynamic specification accounting both for the influence of the lagged binary variable and that of the lagged index takes the form of: [6]

$$\mathrm{P}_{t-1}(y_t = 1) = \Lambda(\pi_t) = \Lambda(\alpha\pi_{t-1} + \delta y_{t-1} + x_{t-1}\beta), \tag{1}$$

where $\mathrm{P}_{t-1}(y_t = 1)$ is the conditional probability given the information set we have at our disposal at time $t-1$ and π_t is the index at time t.

Actually, this is the first representation of Kauppi and Saikonnen (2008) applied to EWS models. The main advantage of this general framework is that it allows to estimate and then compare different alternative specifications. More precisely, we first consider the pure static model, in which the occurrence of currency crises is explained only by exogenous macroeconomic variables. Second, a dynamic model including the lagged value of the binary dependent variable y_{t-1} is proposed. Third, a dynamic model including the lagged index π_{t-1} is implemented. Finally, the most complex dynamic model, including both the lagged dependent variable y_{t-1} and the lagged index π_{t-1} is estimated. Given the maximum-likelihood framework, these dynamic time-series models are easy to implement using any existing econometric software. [7] Besides, the ML estimators have the desired large-sample properties. In fact, the log-likelihood function takes the general form of:

$$\mathrm{LogL}(\theta) = \sum_{t=1}^{T} l_t(\theta) = \sum_{t=1}^{T} [y_t log\Lambda(\pi_t(\theta)) + (1 - y_t) log(1 - \Lambda(\pi_t(\theta)))], \tag{2}$$

where θ is the vector of parameters.

Nevertheless, one should not loose sight of the fact that since in the last two models α is an autoregressive parameter, it has to satisfy the usual stationarity condition, *i.e.*, the roots of the corresponding polynomial lie outside the unit circle. To tackle this problem, a constrained maximum likelihood estimation [8] is implemented and described in Appendix 1.

6. It can be noted that the model for h-step-ahead forecasts can be obtained by repetitive substitutions. For more details, see Kauppi and Saikonnen (2008).

7. All the codes have been written in Matlab and are available from the authors upon request.

8. Besides, we tackle the autocorrelation problem induced by the construction of a j months ahead crisis variable by considering a Gallant correction for the variance-covariance matrix.

2.2 Panel Data Analysis

Instead of considering EWS for individual countries and hence applying a time-series approach, several papers (Berg and Patillo, 1998; Kumar et al., 2003) favor a panel data approach by pooling the information available in several countries. The main advantage of using panel data methods is the number of observations which increases the ability to estimate. Nevertheless, as shown by Berg et al. (2008), pooling all possible countries can be problematic for heterogenous countries. Thus, it is advisable to perform pre-cluster samples of countries. Here we present a dynamic version of a fixed effect panel model by elaborating on Carro (2007).

Let us consider here the panel version of the dynamic limited dependent EWS which has the following form:

$$\mathrm{P}(y_{it} = 1) = \Lambda(\alpha y_{it-1} + \beta x_{it-1} + \eta_i), \ t = 0, 1, 2, ...T, \text{ and } i = 1, 2, ..N, \tag{3}$$

where N is the number of individuals in the panel, T represents the number of time series observations for each individual, and η_i accounts for the permanent unobserved heterogeneity between individuals. Since we do not impose any distributional assumption to η_i, $i = 1, 2, ..N$, they are treated as parameters to be estimated, and our approach is one with fixed effects. The dependent variable y_{it} equals 1 if if there will be at least a crisis in the following j months and it equals 0 in the opposite case. Moreover, x_{it-1} represents the matrix of explicative variables, which can include besides macroeconomic variables the lagged index as well.

The log-likelihood of the model conditioned on the first observation, often called concentrated likelihood takes the following form:

$$\mathrm{LogL}(\theta, \eta_i) = \sum_{i=1}^{N} \mathrm{LogL}_i(\theta, \eta_i) = \sum_{i=1}^{N} \sum_{t=1}^{T} [y_{it} ln(\Lambda_{it}) + (1 - y_{it})(1 - \Lambda_{it})], \tag{4}$$

where $\theta = (\alpha, \beta)'$. As usual, the estimated parameters maximize the log-likelihood function, which means that they solve the first order conditions with respect to θ and with respect to η_i. Most importantly, the estimation of θ depends on $\hat{\eta}_i$, which means that $\hat{\theta}$ is a convergent estimator of θ_0 only when $\hat{\eta}_i$ is a convergent estimator of η_{i0}, that is when $N \to \infty$. Thus, the central issue here, as in any non-linear panel model with fixed effects, is how to deal with this incidental parameters problem.

The solution proposed by Carro (2007) actually consists in a numerical substitution of the fixed effects (η_i) in the estimation of θ. Thus, at each step N non-linear equations are solved so as to estimate $\hat{\eta}_i$, $i = 1, 2...N$ by using $\hat{\theta}$ obtained at the previous step and then the estimated values of $\hat{\eta}_i$ are introduced into the first order condition corresponding to the concentrated likelihood so as to estimate $\hat{\theta}$. To be more precise, the estimation of η is nested in the algorithm that maximizes the concentrated log-likelihood, so that at each iteration $N+1$ non-linear optimizations are realized using the Gauss-Newton algorithm (the first N optimizations correspond to the fixed effects, while the last one corresponds to the θ parameters).

Moreover, in order to reduce the estimation bias from $O(T^{-1})$ to $O(T^{-2})$ without increasing the asymptotic variance, Carro proposed a modification of the first order condition expressed in terms of the original parameters of the model (hereafter MMLE). Consequently, the modified score for a certain country takes the following form:

$$\begin{aligned} d_{\theta Mi}(\theta) = d_{\theta Ci}(\theta, \hat{\eta}_i(\theta)) - \frac{1}{2}\frac{1}{d_{\eta\eta i(\theta,\hat{\eta}_i(\theta))}}\left(d_{\theta\eta\eta i(\theta,\hat{\eta}_i(\theta))} + d_{\eta\eta\eta i(\theta,\hat{\eta}_i(\theta))}\frac{\partial\hat{\eta}_i(\theta)}{\partial\theta}\right) \\ +\frac{\partial/\partial\eta_i(E[d_{\theta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i])}{E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}|_{\eta_i=\hat{\eta}_i(\theta)} - \frac{E[d_{\theta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}{E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}|_{\eta_i=\hat{\eta}_i(\theta)} \\ *\frac{\partial/\partial\eta_i(E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i])}{E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}|_{\eta_i=\hat{\eta}_i(\theta)}, \end{aligned} \tag{5}$$

where $d_{\theta Ci}(\theta, \hat{\eta}_i(\theta))$ is an individual's score from the concentrated likelihood (hereafter MLE):

$$d_{\theta Ci}(\theta, \hat{\eta}_i(\theta)) = \frac{y_{it} - F_{it}(\theta,\eta_i)}{F_{it}(\theta,\eta_i)(1-F_{it}(\theta,\eta_i))}\left(y_{it} + \frac{\partial\hat{\eta}_i(\theta)}{\partial\theta}\right). \tag{6}$$

The MMLE first order condition corresponding to the entire panel can be obtained by adding the individual MMLE scores.

At the same time, the corresponding standard errors can be easily obtained from the principal diagonal of the variance-covariance matrix, which is given by the inverse of the Hessian accounting for the fixed effects. The computation of the modified score and Hessian matrix is detailed in Appendix 2.

The main advantage of Carro's (2007) estimation method consists in its simplicity of implementation since it is based on the first derivatives of the log-likelihood function. At the same time, it allows for the estimation of all the dynamic specifications introduced in the previous subsection. Finally, given the reduction of the bias, the estimators have good asymptotic properties. [9]

3 Empirical Application

To compare the forecasting abilities of static and dynamic currency crises EWS, both time-series and panel models are estimated in order to retrieve the one-step ahead crisis probabilities. Then, using the validation framework proposed by Candelon et al. (2009), the

9. All the codes have been developed in Matlab and are available upon request.

best specification is selected and its forecasting performances are assessed : First, we proceed to an in-sample analysis using the entire database so as to identify the outperforming model. Second, aiming to assess the out-of-sample predictive abilities of the best model, we use a rolling windows procedure with a view to obtain out-of-sample forecasts.

Nevertheless, before starting the analysis *per se*, let us present some data-related issues.

3.1 Data

Monthly data expressed in US dollars covering the period 1985-2008 for 15 emerging countries [10] have been extracted from the IMF-IFS database as well as the national banks of the countries under analysis via Datastream. Several explanatory variables from two economic sectors were selected (see Candelon et al. 2009, Berg et al., (2008), Lestano et al., 2003).

1. External sector: the one-year growth rate of international reserves, the one-year growth rate of imports, the one-year growth rate of exports, the ratio of M2 to foreign reserves, and the one-year growth rate of M2 to foreign reserves.

2. Financial sector: the one-year growth rate of M2 multiplier, the one-year growth rate of domestic credit over GDP, real interest rate and real exchange rate overvaluation.

As in Kumar (2003), we dampen every variable using the formula : $f(x_t) = sign(x_t) * ln(1 + |x_t|)$, so as to reduce the impact of extreme values. Traditional first generation (Im, Pesaran, Shin, 1997) as well as MW (Maddala and Wu 1999) and second generation (Bai and Ng, 2001 and Pesaran, 2003) panel unit root tests are performed, leading to the rejection of the null hypothesis of stochastic trend for all explanatory variables. Besides, the gaps through the series are replaced with the mean value of each series.

Since we aim to evaluate the forecasting abilities of dynamic logit models, we proceed to a general selection from the aforementioned exogenous variables, leading to the choice of only two macroeconomic variables. It is the first lag of these variables that is introduced into the models as a control variable, namely the one-year growth rate of international reserves and the one-year growth rate of M2 to foreign reserves. To be more exact, this selection is based on previous results found in the literature, on the correlation between the indicators, as well as on the explanatory power of each variable.

3.2 Dating Currency Crises

The most common method leading to the identification of currency crisis periods implies the computation of an index of speculative pressure. If this index exceeds a certain threshold,

10. Argentina, Brazil, Chile, Indonesia, Israel, Malaysia, Mexico, Morocco, Peru, Philippines, South Korea,Turkey, Thailand, Uruguay and Venezuela.

a crisis episode is identified. As in Candelon et al. (2009), we base our choice on the results of Lestano and Jacobs (2004). Following their results, we identify crisis periods using the KLR modified pressure index (KLRm), which, unlike the KLR index, also includes interest rates:

$$\text{KLRm}_{n,t} = \frac{\Delta e_{n,t}}{e_{n,t}} - \frac{\sigma_e}{\sigma_r}\frac{\Delta r_{n,t}}{r_{n,t}} + \frac{\sigma_e}{\sigma_i}\Delta i_{n,t}, \tag{7}$$

where $e_{n,t}$ denotes the exchange rate (*i.e.,* units of country n's currency per US dollar in period t), $r_{n,t}$ represents the foreign reserves of country n in period t, while $i_{n,t}$ is the interest rate in country n at time t. Meanwhile, the standard deviations σ_X are actually the standard deviations of the relative changes in the variables $\sigma_{(\Delta X_{n,t}/X_{n,t})}$, where X denotes each variable separately, including the exchange rate, foreign reserves, and the interest rate, with $\Delta X_{n,t} = X_{n,t} - X_{n,t-6}$.[11] For both subsamples, the threshold equals two standard deviations above the mean:[12]

$$Crisis_{n,t} = \begin{cases} 1, & \text{if KLRm}_{n,t} > 2\sigma_{\text{KLRm}_{n,t}} + \mu_{\text{KLRm}_{n,t}} \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

3.3 Optimal Country Clusters

As Berg et al. (2008) have pointed out, pooling all available countries into one panel model might not be the best alternative especially in terms of forecasting abilities of the model. Nevertheless, a viable alternative to time-series estimation might be represented by a panel including only poolable countries. To be more precise, by poolable countries we mean a group of countries for which the slope parameters corresponding to the time-series models are statistically equal to the ones of a panel model including the same group of countries, *i.e.*, $\beta_i = \beta_p$, where β_i is the vector of parameters for country i and β_p is the vector of parameters corresponding to the panel model. It is Kapetanios (2003) who proposed a sequential procedure based on an Hausman type statistic that tests the homogeneity of parameters between different countries grouped together in the same panel. Thus, it allows to isolate country clusters for which the null hypothesis of homogeneity of parameters cannot be rejected.

Following their recommendations, we apply the dynamic panel model on two optimal clusters (11 and respectively 2 countries out of 15) which are identified by using Kapetanios's methodology (Kapetanios, 2003). For the two non-poolable countries (Israel and South Korea) only time-series models are estimated.

11. Additionally, we take into account the existence of higher volatility in periods of high inflation, and consequently the sample is split into high and low inflation periods. The cut-off corresponds to a six month inflation rate higher than 50%.

12. The variable $Crisis$ corresponds to y_t from our general framework.

3.4 Estimation Results

In this subsection we first estimate different time-series models for each country and then, based on the Schwarz Information Criterion (hereafter SBC) we select the most parsimonious dynamic specification. Then, panel models corresponding to the best dynamic time-series model specification are estimated by using the whole sample of countries and respectively, by relying only on the poolable ones.

insert Tables **??**, **??** and **??**

Tables **??**, **??** and **??** show the results of the ML estimates for the four time-series model specifications, *i.e.*, the static model (Model 1), a dynamic one including the *lagged binary* dependent variable (Model 2), a dynamic one including the *lagged index* (Model 3), and last but not least, a dynamic model which includes both the *lagged binary* dependent variable and the *lagged index* (Model 4).

The goodness of fit indicator reveals that the independent variables have important explanatory power especially when the lagged dependent variable and/or the lagged index are present in the model, *i.e.*, the dynamic models (see Table **??**).

insert Table **??**

More specifically, the lowest values of the SBC criterion are registered most of the time for these dynamic models and in particular for the second model, which seems to be the most adequate dynamic specification for most of the countries. [13] To put it another way, the goodness of fit indicator is a clear indication of the fact that dynamic specifications generally outperform the static one. Nevertheless, a proper statistical assessment framework for the forecasting performance of static and dynamic models needs to be implemented, which is done in the next section.

At the same time, the signs of the estimated parameters in the best dynamic model, *i.e.*, the second one, tend to correspond to a priori expectations. If an increase in a country's *growth of international reserves* indicator is observed at a certain moment in time, a decline in the probability of occurrence of currency crises is presumed, since it is perceived as an indicator of currency non-vulnerability, *i.e.*, a negative coefficient of the *growth of international reserves* is awaited. Besides, the probability of currency-crisis emergence is supposed to escalate if an expansion of the *growth of M2 to reserves* is noticed in the previous period. To be more exact, if the growth of the amount of money in circulation overruns the *growth of*

13. Nevertheless, the third model seems better for countries like Brazil and Thailand, whereas the static model seems more parsimonious than the dynamic specifications for the countries registering a very small number of crisis periods (only one or two periods), countries for which no model can actually work well since we face a rare event data problem.

international reserves, the currency is perceived as unstable and a speculative attack is foreseeable. Thus, a positive coefficient of the *growth of M2 to reserves* is expected. Nonetheless, several countries register strange signs, *i.e.* negative and significative coefficients.

To sum up, the coefficient of the lagged binary dependent variable is most of the time significant and has a positive sign (except for the countries for which the static model turns to perform better), whereas the impact of macroeconomic variables and of the lagged index is different from one country to another (in terms of sign and significance), emphasizing the idea that accounting for the dynamics of the crisis is compulsory for the construction of a stringent EWS.

Since the second model appears to outperform the other dynamic specifications, we opt for the dynamic panel methodology in the form including the *lagged binary* dependent variable along with the selected macroeconomic indicators.

The results of the estimation of a dynamic panel logit model with fixed effects using the entire database and respectively using only the poolable countries are reported in Table **??**. It can be noticed that the signs of the coefficients are similar from one model to another, and that most of them are significative for all the significance levels, *i.e.*, 1%, 5% and 10%. And yet, the coefficient of the *growth of M2 to reserves* has the wrong sign for the panel including all the countries as well as for the first cluster of poolable countries, supporting the conclusion of Berg et al. (2008) that only poolable countries should be grouped together in a panel framework.

4 Forecasts Evaluation

So far we have seen that accounting for the currency crisis dynamics matters, and more exactly we have proved that the introduction of the lagged binary dependent variable into the model improves the estimation of currency crises probabilities. In this section we go one step further and statistically test the in-sample one-step-ahead forecasting abilities of the static and dynamic currency crisis EWS models by applying the validation methodology developed in Candelon et al. 2009. [14] Then, the out-of-sample one-step ahead predictive abilities of the best model are checked. Finally, a robustness check is performed considering an horizon of 24 months for the out-of-sample forecast.

14. It consists in a 3-step approach: First, the optimal cut-off for each country based on an accuracy-error measures. Second, the predictive abilities of the two type of models is scrutinized. using criteria such as AUC, QPS, LPS, Kuiper's Score, Pietra Index and the Bayesian Error rate. Third, comparison tests are implemented so as to identify the outperforming model. To be more precise, a Clark-West test (Clark and West, 2007) is used in the case of nested models, while a Diebold-Mariano (Diebold and Mariano, 1995) test is utilized for non-nested models.

4.1 Time-series Models

In this part of the paper, we check the within sample forecasting abilities of the static and dynamic time-series models. For this purpose, the whole dataset is considered (January 1986 - February 2008). Moreover, for comparability reasons, we gauge the forecasting abilities of dynamic Markov switching models. To this aim, a Markov-switching model is estimated for each country (see Abiad, 2003; Arias and Erlandson, 2005; Candelon et al. 2009). Nevertheless, contrary to the static model that has been previously used, our approach is based on a dynamic perspective, materialized in a switch of the lagged binary dependent variable from one regime to another, *i.e.*, from crisis to calm periods and vice-versa. Once the filtered probabilities are computed, the model for each country is evaluated.

First of all, the optimal cut-offs as well as the percentage of correctly forecasted crises (sensitivity) and respectively calm periods (specificity) are available in Table **??**.

insert Table **??**

The optimal cut-off for each country has been identified by relying on the accuracy and error measures thus giving more weight to the correct identification of crises periods (sensitivity). Table **??** shows that both the static and dynamic country per country models are characterized by small values of the cut-offs (they range between 0.008 and 0.606). Moreover, both crisis and calm periods are very well forecasted by the dynamic logit model, *i.e.*, sensitivity and specificity lay between 66.7% and 100% for each country while in the case of the static model they range between 50% and 100%. This means that the lagged dependent variable has improved explanatory power and discriminates very well between calm and crisis periods.

Indeed, for most of the countries the crisis probabilities issued from the dynamic logit model are quite low during real calm periods and they are very high in the real crises periods (see Figure 1 and 2), reinforcing the idea that the dynamic model outperforms the static one. To be more precise, this model correctly forecasts most of the currency crisis episodes that been recorded and analyzed by other studies (Abiad, 1993; Dabrowski, 2003; Glick and Hutchison, 1999) as well as more recent ones, while the static model seems to be less efficient.

At the same time, the *sensitivity* and $specificity$ of the dynamic Markov model vary a lot from one country to another, *i.e.* they sometimes reach their maximum, 1, but other times they drop to their minimum, 0, as well, indicating that dynamic Markov models may not be as good as the logit ones are. To confirm this intuition, a proper comparison test will be implemented further on.

Next, performance assessment criteria based on both sensitivity-specificity measures (AUC, Kuiper's score, Pietra index, Bayesian Error rate) and on the comparison of forecasts with the realizations of the crisis variable (QPS and LPS) are used. We recall that the higher the value of AUC is the better the model will be; a positive value of Kuiper's score signifies that the model generates more hits than false alarms, and so its predictive performance should increase; similarly, a higher Pietra index, and a lower Bayesian error rate indicate a more stringent model, as do values of QPS and LPS closer to zero.

insert Tables **??** and **??**

On the one hand, the results corresponding to the static time-series model are presented in the upper part of Table **??**. By comparison with the results of the dynamic logit model (see the lower part of the Table **??**), it seems that the values of the evaluation criteria of the static model are not as close to the optimum as for the dynamic model. The difference is most of the time at the second decimal, and it favors our dynamic specification.

On the other hand, the forecasting abilities of dynamic Markov models seem to vary a lot from one country to another (see Table **??**); for example, QPS and LPS have relatively high values, while AUC is sometimes worst than the one of a random model. These findings support our intuition that the dynamic Markov model is not even as good as the static logit.

Finally, the optimal model specification is identified by applying Clark-West's MSPE-adj test and Diebold Mariano's DM test. First, the two time-series models are compared using Clark and West, (2007) test, suited to nested models, then, the test developed by Diebold-Mariano, (1995) is implemented so as to compare logit and Markov models. The results obtained are presented in Table **??**.

insert Table **??**

Table **??** reveals that the dynamic time-series specification outperforms the static one for most of the countries.[15] Indeed, Clark-West's test rejects the null hypothesis of equal forecasting abilities for 10 out of the 15 countries. The results of these tests corroborate our main finding that the lagged binary dependent variable matters for the forecasting abilities of currency crises EWS models. Moreover, the middle part of Table **??** confirms the findings of Candelon et al. (2009) stressing the forecasting superiority of the logit models versus the dynamic Markov models.

4.2 Panel Models

So far, we have shown that time-series dynamic logit models outperform both static logit models and dynamic Markov switching specifications. Now, the two dynamic panel models considered in the paper (based on all available countries and respectively using only the

15. As we have already seen in the information criterion Table, that there are several countries for which the static model seems better than the dynamic. Here we have the statistical proof that for Brazil, Chile, Israel, South Korea and Morocco the static and dynamic models have similar forecasting abilities.

poolable ones) are evaluated and their in sample forecasting abilities compared to those of the best time-series specification, *i.e.*, the dynamic logit model including the lagged binary dependent variable.

insert Table **??**

First of all, in the case of the dynamic panel models the values of the optimal cut-off are similar to the ones registered for the dynamic time-series logit models, even though fairly smaller *i.e.*, they vary between 0.001 and 0.74 (see Table **??**). Similarly, *sensitivity* and *specificity* values corresponding to the two types of dynamic models resemble. All in all, the results obtained by using a panel model do not seem to diverge much from those obtained when using time-series models. To check this intuition, proper statistical comparison tests are applied at the end of this section.

insert Table **??**

Second, Table **??** shows that the dynamic panel models generally have good forecasting abilities. To be more precise, with the exception of Chile, Morocco and Uruguay, the AUC is always greater than 0.8, Kuiper's score has positive values, Pietra index registers relatively high values, while the Bayesian Error rate, QPS and LPS are very close to 0 (inferior to 0.153 to be more exact). Besides, the results are very similar from one dynamic model to another except for Uruguay, for which the results cluster estimation are worst than the ones corresponding to the entire dataset.

Last but not least, the two dynamic panel models are compared to the time-series dynamic one and to the dynamic Markov-switching specification by using the DM test proposed by Diebold-Mariano (1995).

insert Table **??**

Table **??** shows that the null hypothesis of equal forecasting abilities cannot be rejected, thus clarifying the fact that the dynamic panel models do not have better forecasting abilities than the dynamic time series one, supporting the results obtained by Berg et al (2008). The only exceptions are Marocco and Venezuela. Besides, the right part of Table **??** proves that not only time-series dynamic logit models but also dynamic panel logit models are better than dynamic Markov-switching specifications.

4.3 Out-of-sample analysis

In the previous subsections the properties of the dynamic logit model including the lagged binary dependent variable have been investigated. Nevertheless, the out-of-sample characteristics of such an EWS model have to be checked before concluding.

To this aim, an out-of-sample experiment using a rolling windows procedure has been implemented. More precisely, in order to compute the probability of having a crisis in January 1997, a dynamic time-series logit model is estimated using the dataset from January 1986 to December 1996 and the parameters obtained are used to calculate the crisis probability for January 1997. Similarly, for February 1997, the in-sample data corresponds to the February 1986-January 1997 period, and so on. A series of out-of-sample crisis probabilities is thus obtained for each country so that the aforementioned evaluation methodology can be applied straightforward.

Figure 3 presents the out-of-sample crisis probabilities from January 1997 to February 2008 for each of the 11 countries registering at least one crisis for the in-sample period (January 1986 - December 1996). [16] It appears that for the countries which faced more than one month of currency crisis, the EWS forecasting probability is very low in calm periods while it is very high during crisis periods. It hence follows closely the in-sample results. On the contrary, when countries faced only one period of crisis, forecasting abilities are disappointing. Such a result is driven by the low amount of crisis observations : the number of 0 is huge, hence causing bias in the estimation of the dynamic logit model. Thus, this findings would support the use of longer forecast horizons as it is usually done in the literature. Considering a forecast horizon of j months increases "artificially" the number of 1 observation in the sample, which improves the quality of the estimation and hence of the forecasting ability. Nevertheless, it also introduced autocorrelation (see Berg and Coke, 2004) which may be problematic.

Consequently, a robustness check is performed by employing the $C24$ crisis variable. Figures 4 and 5 present the out-of-sample probabilities corresponding to this new binary variable. This time the results are excellent, since the crisis probability is very high in real crisis periods while it is very low in real calm periods. Even for the countries which never faced a crisis the results are quite spectacular since the crisis probability is always low. Indonesia and Thailand are the only exceptions, for which a high probability pick can be observed in a calm period. Nevertheless, the picks are not persistent and thus, they can hardly be perceived as signals of crisis. Besides, results are available for all countries, since, contrary to the previous case, they all face currency crises in the within-sample period.

To summarize, it seems that all the EWS considering a forecast horizon j, where $j > 1$ should be dynamic, since the autocorrelation can be successfully captured improving hence the forecasting abilities of the EWS model.

The cutoffs used for the out-of-sample series of crisis probabilities in both cases (crisis at time t and respectively in 24 months) are reported in Table **??**, while the out-of-sample validation results are displayed in Table **??**. The superiority of the forecasting results corres-

16. If there is not any in-sample crisis, we cannot compute the optimal cut-off needed in order to evaluate the out-of-sample forecasting abilities of the model.

ponding to the C24 variable is clear. Sensitivity and specificity are always higher than the ones corresponding to the crisis at time t variable. Similarly, AUC, Kuiper's score, Pietra index and Bayesian error rate are higher while QPS and LPS are lower for C24.

insert Tables **??** and **??**

5 Conclusion

This paper provides evidence of the importance of crisis dynamics to adequately forecast crises and shows that future EWS models should integrate this dynamic. It is actually the first to consider an exact ML methodology, elaborated on Kauppi and Saikonnen (2008), to estimate a dynamic limited dependent EWS. In a second part, it extends this methodology to panel by drawing on the works of Carro (2007).

Several conclusions can be drawn from the empirical application of this methodology to construct currency crisis EWS models. First, we show that dynamic logit models consistently outperform static ones as well as MS. This conclusion is drawn from the within sample forecast exercise. Such a result is corroborated by the out-of-sample forecast exercise performed by considering an horizon larger than 1. This can be explained by the fact that dynamic captures the autocorrelation observe in such EWS. Second, looking at their forecasting ability, it turns out that dynamic EWS deliver extremely good forecasting probabilities: close to 1 in the crisis periods or and near 0 the rest of the time.

There is no doubt that in the quest for a new generation for financial crisis EWS, dynamics should constitute a key characteristic that would deliver more adequate signals to prevent financial turmoils. Let us hope that policy makers could exploit these signals to tame such painful events.

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Appendix 1: Constrained Maximum Likelihood Estimation (Kauppi and Saikkonen, 2008)

Let us recall the general form of the model: $\mathrm{P}_{t-1}(y_t = 1) = \Lambda(\alpha\pi_{t-1} + \delta y_{t-1} + x_{t-1}\beta)$. Following Kauppi and Saikkonen, we set the initial value π_0 to $(\bar{x}\beta)/(1-\alpha)$, $\bar{x}$ being the sample mean of the exogenous variables. The initial condition for the β vector of parameters is given by an OLS estimation, while the initial α is set to 0. Moreover, since α is an autoregressive parameter, a constrained maximum likelihood estimation must be implemented. Nevertheless, the same results can be reached in a faster and easier way, by using a transformation of the α parameter in the classical maximum likelihood process. Thus, to solve this problem, we denote by ψ the new maximization parameter, identified so that α is equal to $\psi/(1+|\psi|)$, *i.e.*, α takes values in the interval [0,1].

Hence, the log-likelihood function takes the form of:

$$\mathrm{LogL}(\theta) = \sum_{t=1}^{T} l_t(\theta) = \sum_{t=1}^{T} [y_t log\Lambda(\pi_t(\theta)) + (1-y_t) log(1-\Lambda(\pi_t(\theta)))], \tag{9}$$

where θ is the vector of parameters $\theta = [\psi \ \beta]$.

It is noticed that in view of the parameter transformation from α to ψ, the maximization variance-covariance matrix corresponds to the parameters $[\beta \ \psi]$, and not to the initial parameters $[\beta \ \alpha]$. Thus, we must proceed to a change of the variance-covariance matrix from the first space to the second one. To this end, we use Taylor's theorem to calculate the approximation of the transformation function around the point ψ_0. To be more exact, since the estimated parameter $\hat{\alpha} = f(\hat{\psi})$, where $f(\hat{\psi}) = \hat{\psi}/(1+|\hat{\psi}|)$, the approximation becomes:

$$\hat{\alpha} = f(\hat{\psi}) \simeq f(\psi_0) + \frac{\partial f(\hat{\psi})'}{\partial \psi}|_{\psi_0}(\hat{\psi} - \psi_0). \tag{10}$$

Nevertheless, we aim at finding the variance of α, and thus, using the formula $Var(a'X) = a'Var(X)a$, we obtain:

$$Var(\hat{\alpha}) \simeq 0 + \frac{\partial f(\hat{\psi})'}{\partial \psi}|_{\psi_0} Var(\hat{\psi}) \frac{\partial f(\hat{\psi})}{\partial \psi}|_{\psi_0} \tag{11}$$

Since $\hat{\psi} \xrightarrow{p} \psi_0$, we can replace ψ_0 with the estimator $\hat{\psi}$ in eq. 8:

$$sVar(\hat{\alpha}) \simeq 0 + \frac{\partial f(\hat{\psi})'}{\partial \psi}|_{\hat{\psi}} Var(\hat{\psi}) \frac{\partial f(\hat{\psi})}{\partial \psi}|_{\hat{\psi}} \tag{12}$$

Last but not least, the first derivative of the transformation function $f(\hat{\psi})$ with respect to $(\hat{\psi})$

can be computed through finite differences. Consequently, the standard errors obtained as the square root of the elements laying on the first diagonal of the variance-covariance matrix are consistent with the $[\alpha \ \psi]$ vector of parameters. More exactly, a Gallant correction based on a Parzen kernel (Gallant, 1987) is used for the variance-covariance matrix. Kauppi and Saikonnen (2008) argue that robust standard errors can be obtained as the diagonal elements of the matrix $\hat{J}(\hat{\theta})^{-1}\hat{I}(\hat{\theta})\hat{J}(\hat{\theta})^{-1}$, where $\hat{I}(\hat{\theta}) = T^{-1}(\sum_{t=1}^{T} \hat{d}_t' \hat{d}_t + \sum_{t=1}^{T} w_{Tj} \sum_{t=j+1}^{T}(\hat{d}_t' \hat{d}_{t-j} + \hat{d}_{t-j}' \hat{d}_t))$, $\hat{d}_t = \partial l_t(\hat{\theta})\partial\theta$, and where $J(\theta) = plim_{T\to\infty} T^{-1} \sum_{t=1}^{T}(\partial^2 l_t(\theta)\partial\theta\partial\theta')$. On top of that, we consider that the robust variance-covariance matrix should be used not only for h-periods-ahead forecasts, $h > 1$ (as in Kauppi and Saikonnen, 2008) but also for one period-ahead forecasts, since the logistic distributional hypothesis imposed to the error term might not always hold and most importantly, since this variance-covariance matrix specification is robust to autocorrelation, automatically introduced when considering an EWS (see Berg and Coke, 2004).

Appendix 2: Modified Maximum Likelihood Estimation (Carro, 2007)

As previously mentioned, the dynamic panel logit models with fixed effects is estimated by solving $N+1$ non-linear equations based on the modified score of each individual, which takes the following form:

$$\begin{aligned} d_{\theta Mi}(\theta) = {} & d_{\theta Ci}(\theta, \hat{\eta}_i(\theta)) - \frac{1}{2}\frac{1}{d_{\eta\eta i(\theta,\hat{\eta}_i(\theta))}}\left(d_{\theta\eta\eta i(\theta,\hat{\eta}_i(\theta))} + d_{\eta\eta\eta i(\theta,\hat{\eta}_i(\theta))}\frac{\partial\hat{\eta}_i(\theta)}{\partial\theta}\right) \\ & + \frac{\partial/\partial\eta_i(E[d_{\theta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i])}{E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}|_{\eta_i=\hat{\eta}_i(\theta)} - \frac{E[d_{\theta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}{E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}|_{\eta_i=\hat{\eta}_i(\theta)} \\ & * \frac{\partial/\partial\eta_i(E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i])}{E[d_{\eta\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]}|_{\eta_i=\hat{\eta}_i(\theta)}, \end{aligned} \tag{13}$$

where $d_{\theta Ci}(\theta, \hat{\eta}_i(\theta))$ is an individual's score from the concentrated likelihood (MLE):

$$d_{\theta Ci}(\theta, \hat{\eta}_i(\theta)) = \frac{y_{it} - F_{it}(\theta,\eta_i)}{F_{it}(\theta,\eta_i)(1 - F_{it}(\theta,\eta_i))}\left(y_{it} + \frac{\partial\hat{\eta}_i(\theta)}{\partial\theta}\right) \tag{14}$$

From the first order condition of η_i, $d_{\eta_i}(\theta,\eta_i) = \sum_{t=1}^{T}(y_{it} - F_{it}(\theta,\eta_i))/F_{it}(\theta,\eta_i)(1 - F_{it}(\theta,\eta_i)) = 0$, it can be derived that the estimators $\hat{\eta}_i$, $i = 1, 2, ..., N$ solve the following equation:

$$\sum_{t=1}^{T} y_{it}\frac{f_{it}(\theta,\eta_i)}{F_{it}(\theta,\eta_i)(1 - F_{it}(\theta,\eta_i))} = \sum_{t=1}^{T}\frac{F_{it}(\theta,\eta_i)f_{it}(\theta,\eta_i)}{F_{it}(\theta,\eta_i)(1 - F_{it}(\theta,\eta_i))} \tag{15}$$

Deriving Equation (15) with respect to θ we can obtain $\partial\hat{\eta}_i(\theta)/\partial\theta$:

$$\partial\hat{\eta}_i(\theta)/\partial\theta = -\frac{\sum_{t=1}^{T}\frac{X_i Z}{F_{it}(\theta,\eta_i)^2(1-F_{it}(\theta,\eta_i)^2)}}{\sum_{t=1}^{T}\frac{Z}{F_{it}(\theta,\eta_i)^2(1-F_{it}(\theta,\eta_i)^2)}}, \tag{16}$$

where $X_i = y_{t-1}, x_{i1}, x_{i2}, ..., x_{iK}$, is the explanatory variable corresponding to the $\theta = \alpha, \beta_1, \beta_2, ..., \beta_K$ parameter we analyze, K is the number of explanatory variables, and $Z = y_t[f'_{it}(\theta,\eta_i)F_{it}(\theta,\eta_i)(1-F_{it}(\theta,\eta_i)) - f^2_{it}(\theta,\eta_i)(1-2F_{it}(\theta,\eta_i))] - f^2_{it}(\theta,\eta_i)F^2_{it}(\theta,\eta_i) - F^2_{it}(\theta,\eta_i)(1-F_{it}(\theta,\eta_i))f'_{it}(\theta,\eta_i)$. Let us remind that $F_{it}(\theta,\eta_i)$ is the cumulative distribution function, $f_{it}(\theta,\eta_i)$ is the density function and $f'_{it}(\theta,\eta_i)$ is the first derivative of the density function. Thus, in the case of a logit model $F_{it}(\theta,\eta_i) = exp(\alpha y_{it-1} + x_{it-1}\beta + \eta_i)/(1 + exp(\alpha y_{it-1} + x_{it-1}\beta + \eta_i))$, $f_{it}(\beta,\eta_i) = exp(\alpha y_{it-1} + x_{it-1}\beta + \eta_i)/(1 + exp(\alpha y_{it-1} + x_{it-1}\beta + \eta_i))^2$, and $f'_{it}(\beta,\eta_i) = exp(\alpha y_{it-1} + x_{it-1}\beta + \eta_i)(1 - exp(\alpha y_{it-1} + x_{it-1}\beta + \eta_i))/(1 + exp(\alpha y_{it-1} + x_{it-1}\beta + \eta_i))^3$.

To put it another way, the partial derivative of the η gradient with respect to θ is given by the implicit functions theorem:

$$\partial\hat{\eta}_i(\theta)/\partial\theta_k = -\frac{\partial d_{\eta_i}(\theta,\hat{\eta}_i)/\partial\theta_k}{\partial d_{\eta_i}(\theta,\hat{\eta}_i)/\partial\eta_i}, \tag{17}$$

where k=1,2,...K, K being the number of explanatory variables considered in the model, $\partial d_{\eta_i}(\theta,\hat{\eta}_i)/\partial\theta_k = \partial^2\mathrm{LogL}(\theta,\eta_i)/\partial\eta_i\partial\theta_k|(\theta,\hat{\eta}_i)$, and $\partial d_{\eta_i}(\theta,\hat{\eta}_i)/\partial\eta_i = \partial^2\mathrm{LogL}(\theta,\eta_i)/\partial^2\eta_i|(\theta,\hat{\eta}_i)$. The estimation of the parameters by classical MLE is straightforward since $d_{\theta Ci}(\theta,\hat{\eta}_i(\theta)) = 0$ and $d_{\eta_i}(\theta,\eta_i) = 0$ can be easily computed and solved. However, aiming to reduce the estimation bias, the implementation of MMLE becomes compulsory, for which further information regarding the expectance of the first order condition and the derivatives of this expectance is required.

In view of the MMLE estimation, we derive the following elements for the α parameter, corresponding to the lagged binary variable:

$$d_{\alpha\eta_i}(\theta,\eta_i) = \frac{\partial^2\mathrm{LogL}_i}{\partial\alpha\partial\eta_i} = -\sum_{t=1}^{T} y_{i,t-1}f_{it}(\alpha y_{it-1} + \beta x_i + \eta_i), \tag{18}$$

$$d_{\eta_i\eta_i}(\theta,\eta_i) = \frac{\partial^2\mathrm{LogL}_i}{\partial^2\eta_i} = -\sum_{t=1}^{T} f_{it}(\alpha y_{it-1} + \beta x_i + \eta_i), \tag{19}$$

$$d_{\alpha\eta_i\eta_i}(\theta, \eta_i) = -\sum_{t=1}^{T} y_{i,t-1} f_{it}^{'}(\alpha y_{it-1} + \beta x_i + \eta_i), \tag{20}$$

$$d_{\eta_i\eta_i\eta_i}(\theta, \eta_i) = -\sum_{t=1}^{T} f_{it}^{'}(\alpha y_{it-1} + \beta x_i + \eta_i), \tag{21}$$

where f is the logistic pdf and f' is the first derivative of the logistic pdf.

Next, we aim at calculating the expectation of the derivatives $d_{\alpha\eta_i}$ and $d_{\eta_i\eta_i}$. Thus, in a first step we calculate the probability at time t that a crisis will occur in country i in the next 24 months given the initial value of the binary dependent variable y_{i0}, the fixed effects η_i and the explanatory variables x_i ($Pr(y_{it} = 1|y_{i0}, \eta_i, x_i)$):
$Pr(y_{i1} = 1|y_{i0}, \eta_i, x_i) = F_{it}(\alpha y_{i0} + \beta x_i + \eta_i)$ starting point. For $t > 1$:

$$Pr(y_{it} = 1|y_{i0}, \eta_i, x_i) = Pr(y_{it-1} = 1|y_{i0}, \eta_i, x_i)(F_{it}(\alpha+\beta x_i+\eta_i)-F_{it}(\beta x_i+\eta_i))+F_{it}(\beta x_i+\eta_i). \tag{22}$$

Moreover, $Pr(y_{i0} = 1|y_{i0}, \eta_i, x_i) = y_{i0}$.
In the second step the expectation of the two derivatives can be calculated:

$$E[d_{\alpha\eta_i}(\theta, \eta_i)|y_{i0}, \eta_i, x_i] = -\sum_{t=1}^{T} E[y_{it-1} f_{it}(\alpha y_{it-1} + \beta x_i + \eta_i)|y_{i0}, \eta_i, x_i], \text{ where} \tag{23}$$

$$E[y_{it-1} f_{it}(\alpha y_{it-1} + \beta x_i + \eta_i)|y_{i0}, \eta_i, x_i] = f_{it}(\alpha + \beta x_i + \eta_i) Pr(y_{it-1} = 1|y_{i0}, \eta_i, x_i). \tag{24}$$

and

$$E[d_{\eta_i\eta_i}(\theta, \eta_i)|y_{i0}, \eta_i, x_i] = -\sum_{t=1}^{T} E[f_{it}(\alpha y_{it-1} + \beta x_i + \eta_i)|y_{i0}, \eta_i, x_i], \text{ where} \tag{25}$$

$$\begin{aligned} E[f_{it}(\alpha y_{it-1} + \beta x_i + \eta_i)|y_{i0}, \eta_i, x_i] &= f_{it}(\alpha + \beta x_i + \eta_i) Pr(y_{it-1} = 1|y_{i0}, \eta_i, x_i) \\ &+ f_{it}(\beta x_i + \eta_i)(1 - Pr(y_{it-1} = 1|y_{i0}, \eta_i, x_i)) \\ &= Pr(y_{it-1} = 1|y_{i0}, \eta_i, x_i)(f_{it}(\alpha + \beta x_i + \eta_i) \\ &- f_{it}(\beta x_i + \eta_i)) + f_{it}(\beta x_i + \eta_i), \end{aligned} \tag{26}$$

The last elements needed in the gradient function are the derivatives of the two expectations of $d_{\alpha\eta_i}$ and $d_{\eta_i\eta_i}$ with respect to the fixed effect η_i. Nevertheless, to compute these elements, the derivative of the probability of occurrence of a crisis within 24 months at time t in country i with respect to η_i must be first calculated:

$$\frac{\partial}{\partial \eta_i} Pr(y_{i1}=1|y_{i0},\eta_i,x_i) = f_{i1}(\alpha y_{i0}+\beta x_i+\eta_i) \tag{27}$$

$$\begin{aligned}\frac{\partial}{\partial \eta_i} Pr(y_{it}=1|y_{i0},\eta_i,x_i) = {} & \frac{\partial}{\partial \eta_i} Pr(y_{it-1}=1|y_{i0},\eta_i,x_i)(F_{it}(\alpha+\beta x_i+\eta_i)-F_{it}(\beta x_i+\eta_i)) \\ & + Pr(y_{it}=1|y_{i0},\eta_i,x_i)(f_{it}(\alpha+\beta x_i+\eta_i)-f_{it}(\beta x_i+\eta_i))+f_{it}(\beta x_i+\eta_i).\end{aligned} \tag{28}$$

Finally, the last elements needed in the formula of the gradient are obtained

$$\begin{aligned}\frac{\partial}{\partial \eta_i}(E[d_{\alpha\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]) &= -\sum_{t=1}^{T}\frac{\partial}{\partial \eta_i}E[y_{it-1}f(\alpha y_{it-1}+\beta x_{it-1}+\eta_i)|y_0,\eta_i,x_i] \\ &= f^{'}(\alpha+\beta x_{it-1}+\eta_i)Pr(y_{it-1}=1|y_{i0},\eta_i,x_i) \\ &+ f(\alpha+\beta x_{it-1}+\eta_i)\frac{\partial}{\partial \eta_i}Pr(y_{it-1}=1|y_{i0},\eta_i,x_i),\end{aligned} \tag{29}$$

and respectively

$$\begin{aligned}\frac{\partial}{\partial \eta_i}(E[d_{\eta_i\eta_i}(\theta,\eta_i)|y_{i0},\eta_i,x_i]) &= -\sum_{t=1}^{T}\frac{\partial}{\partial \eta_i}E[f(\alpha y_{it-1}+\beta x_{it-1}+\eta_i)|y_0,\eta_i,x_i] \\ &= \frac{\partial}{\partial \eta_i}Pr(y_{it-1}=1|y_{i0},\eta_i,x_i)(f(\alpha+\beta x_{it-1}+\eta_i)-f(\beta x_{it-1}+\eta_i)) \\ &+ Pr(y_{it-1}=1|y_{i0},\eta_i,x_i)(f^{'}(\alpha+\beta x_{it-1}+\eta_i)-f^{'}(\beta x_{it-1}+\eta_i)) \\ &+ f^{'}(\beta x_{it-1}+\eta_i).\end{aligned} \tag{30}$$

The individual score corresponding to the slope parameters, *i.e.* β, can be computed in a similar way. Nevertheless, we must take into account the fact that $\partial F/\partial \beta_k = x_{it,k}f$, where $x_{it,k}$ is the k^{th} explanatory variable, which is known, contrary to y_{t-1} from the score corresponding to the lagged binary variable parameter α.

As for the variance-covariance matrix, it is the inverse of the the MMLE Hessian matrix, which is calculated accounting for the fixed effects by using the following formula:[17]

$$\begin{aligned}&\sum_{i=1}^{N}(\frac{\partial^2 \text{LogL}_i(\theta,\hat{\eta}_i(\theta))}{\partial\theta\partial\theta}+\frac{\partial^2 \text{LogL}(\theta,\eta_i)}{\partial\theta\partial\eta_i}|_{\eta_i=\hat{\eta}_i(\theta)}\frac{\partial\hat{\eta}_i(\theta)}{\partial\theta} \\ &+[\frac{\partial^2 \text{LogL}_i(\theta,\eta_i(\theta))}{\partial\eta_i\partial\theta}|_{\eta_i=\hat{\eta}_i(\theta)}+\frac{\partial^2 \text{LogL}_i(\theta,\eta_i(\theta))}{\partial\eta_i\partial\eta_i}|_{\eta_i=\hat{\eta}_i(\theta)}\frac{\partial\hat{\eta}_i(\theta)}{\partial\theta}]\frac{\partial\hat{\eta}_i(\theta)}{\partial\theta}).\end{aligned} \tag{31}$$

17. It is also possible to correct for autocorrelation as in the case of time-series models, by using a "sandwich estimator" for the variance-covariance matrix.

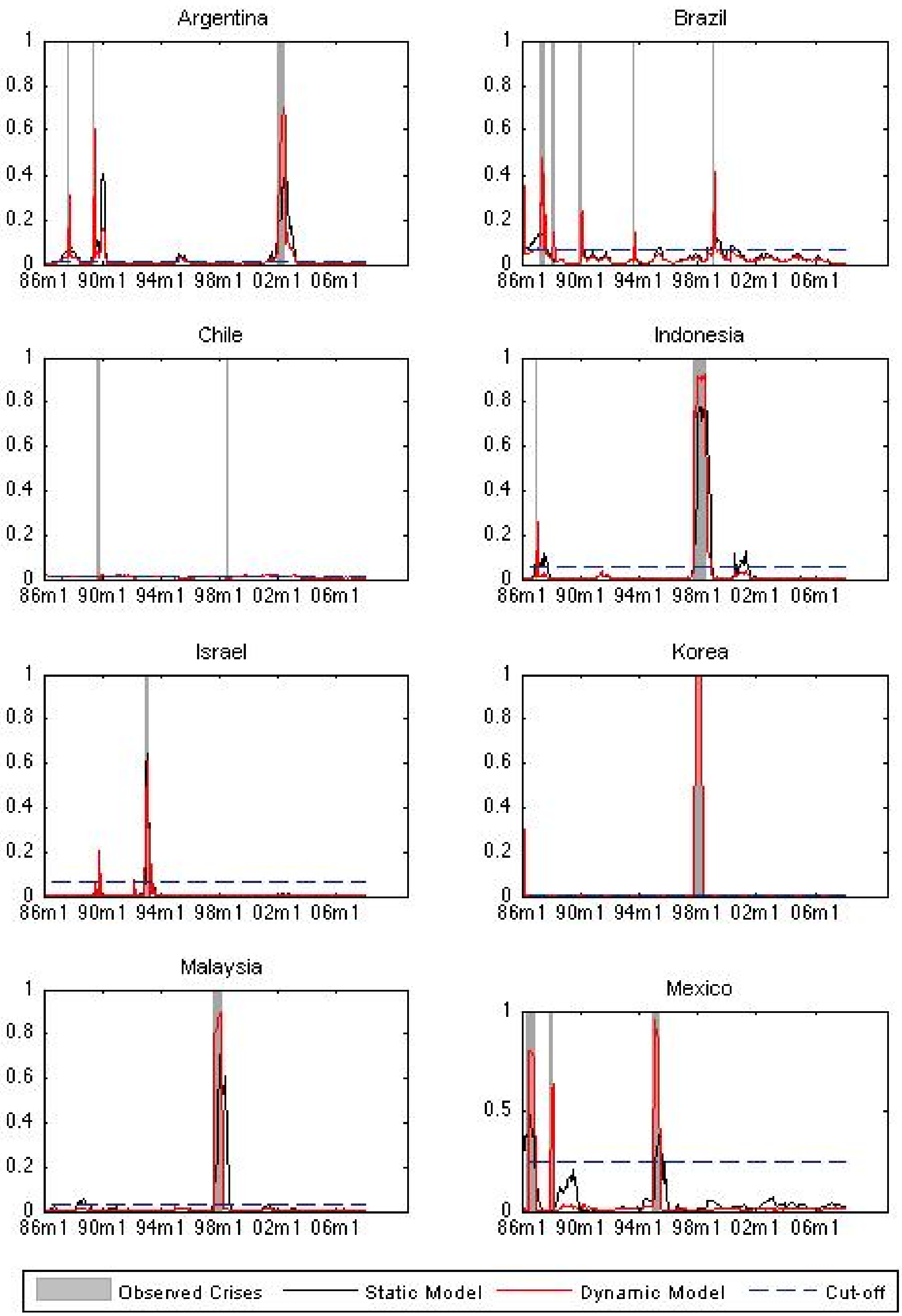

FIGURE 1 – Predicted probability of crisis - in sample

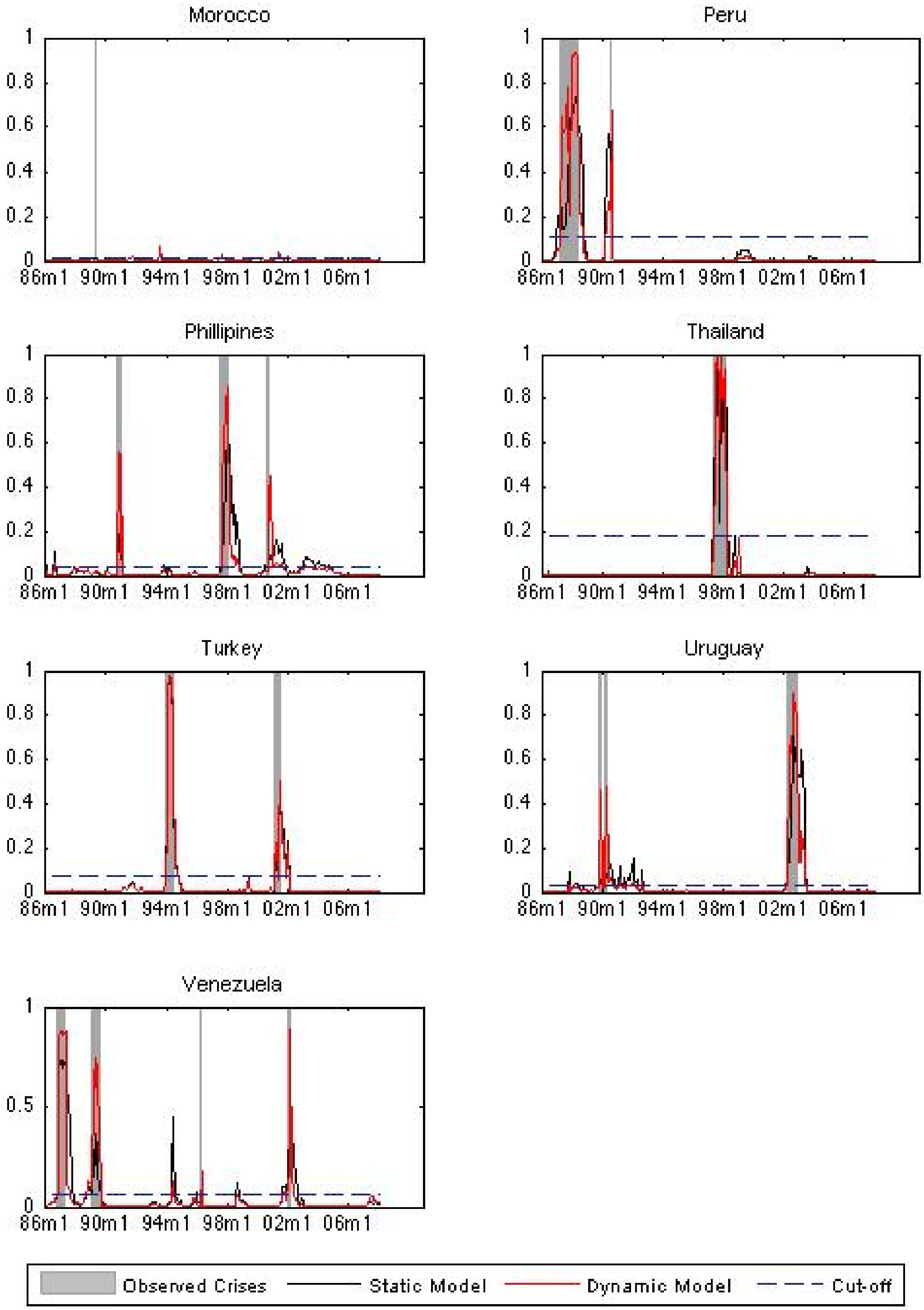

FIGURE 2 – Predicted probability of crisis - in sample (continued)

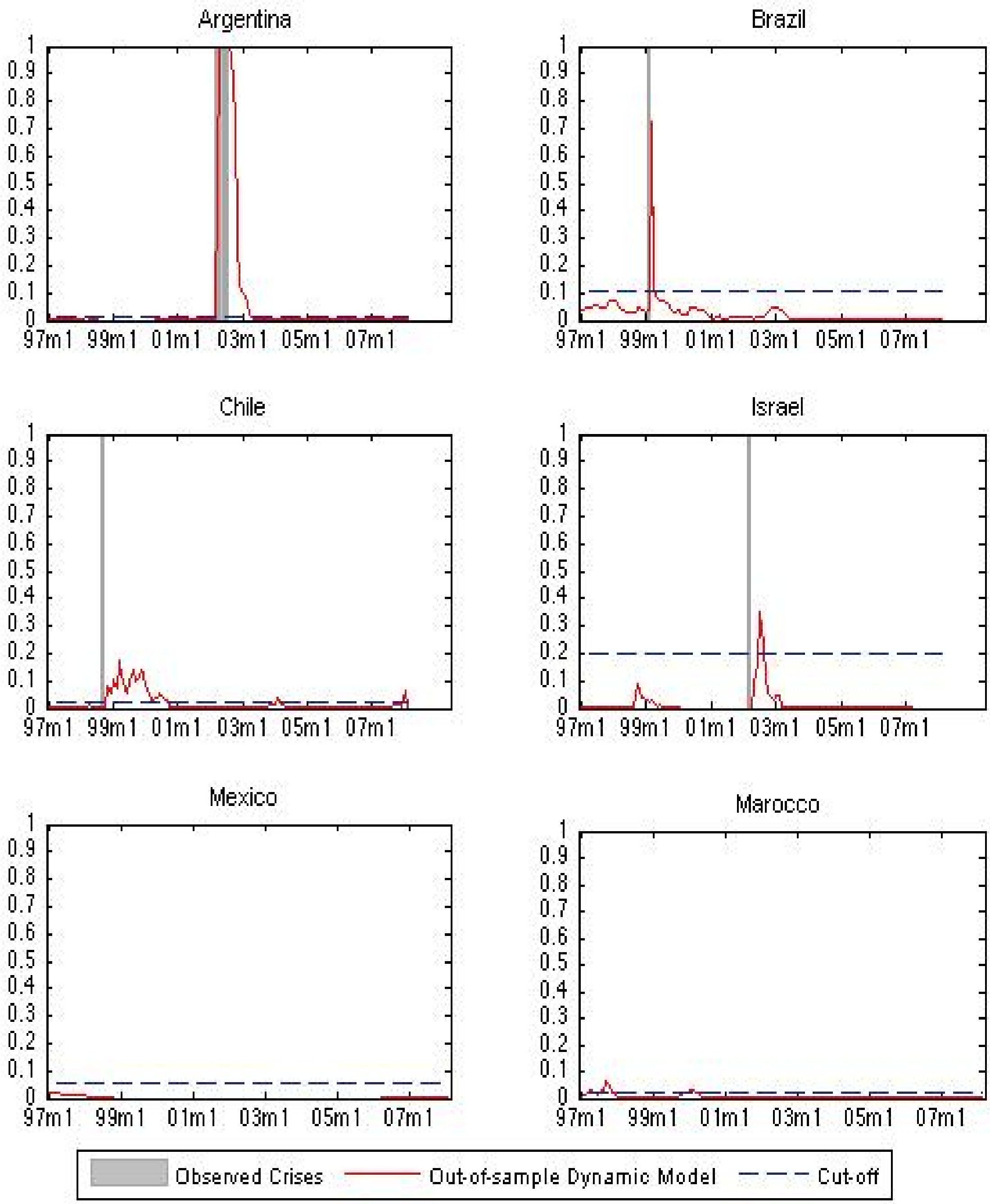

FIGURE 3 – Predicted probability of crisis (one-step-ahead forecasts) - out-of-sample

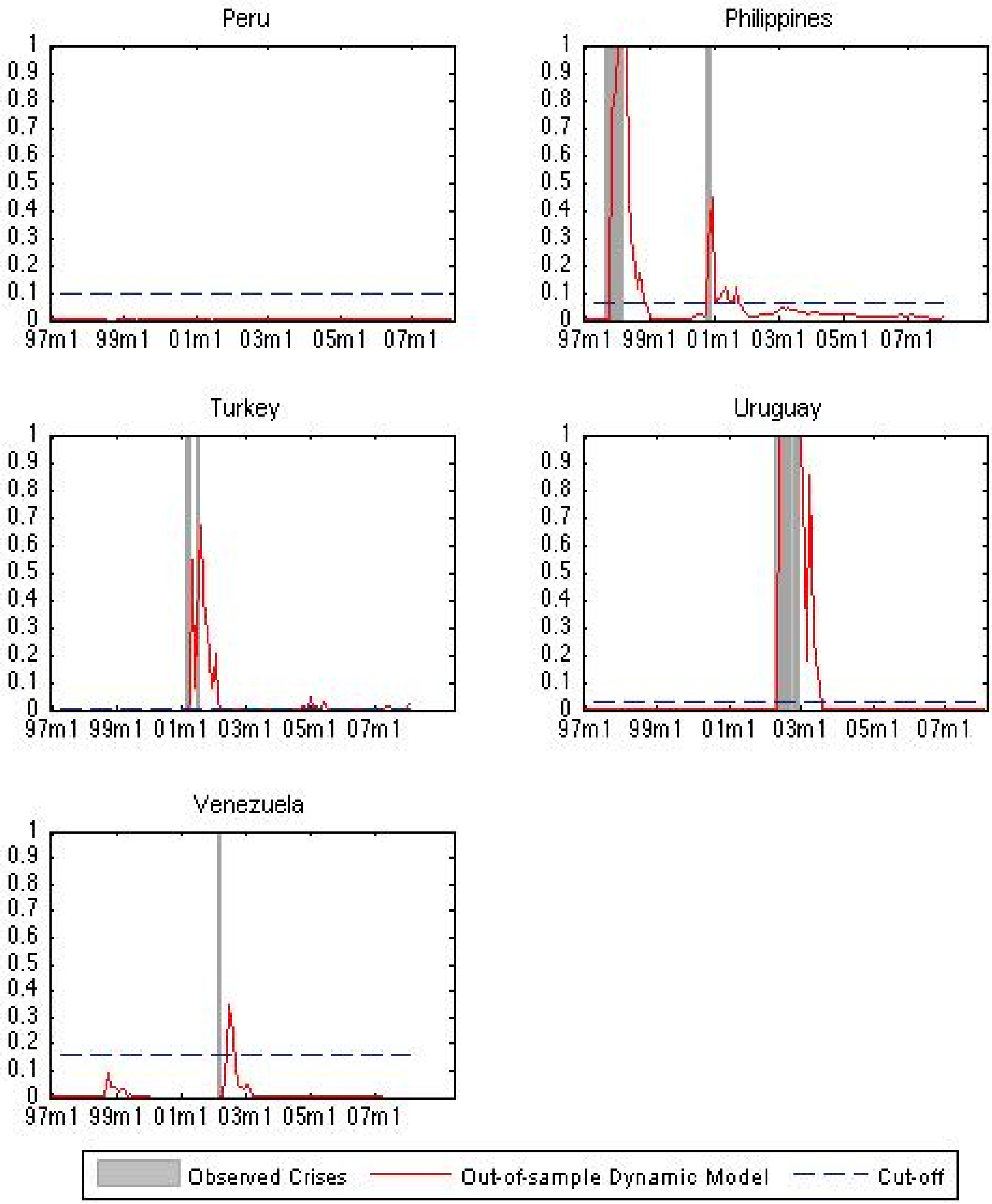

FIGURE 4 – Predicted probability of crisis (one-step-ahead forecasts) - out-of-sample (continued)

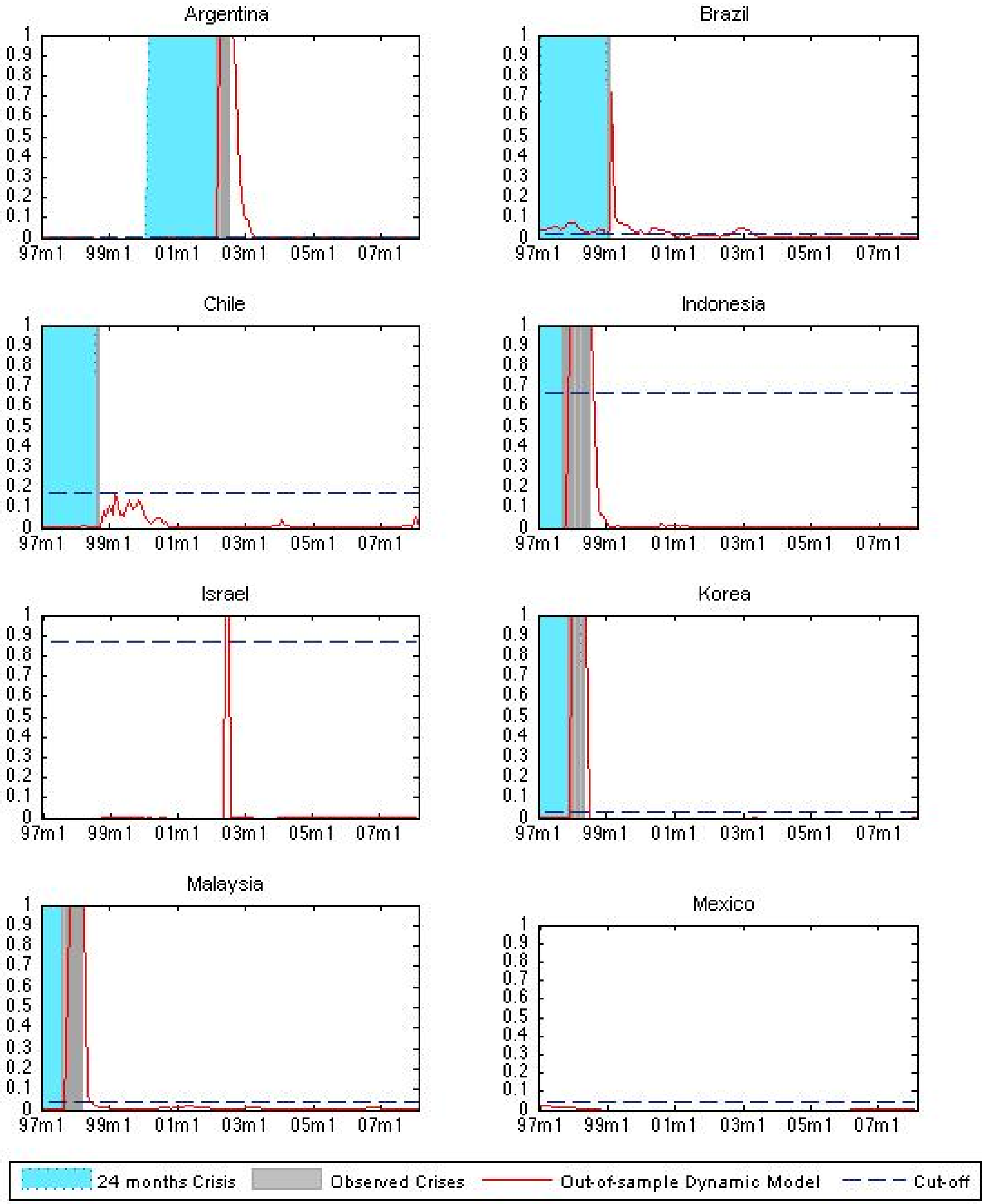

FIGURE 5 – Predicted probability of crisis (24-months-ahead forecasts) - out-of-sample

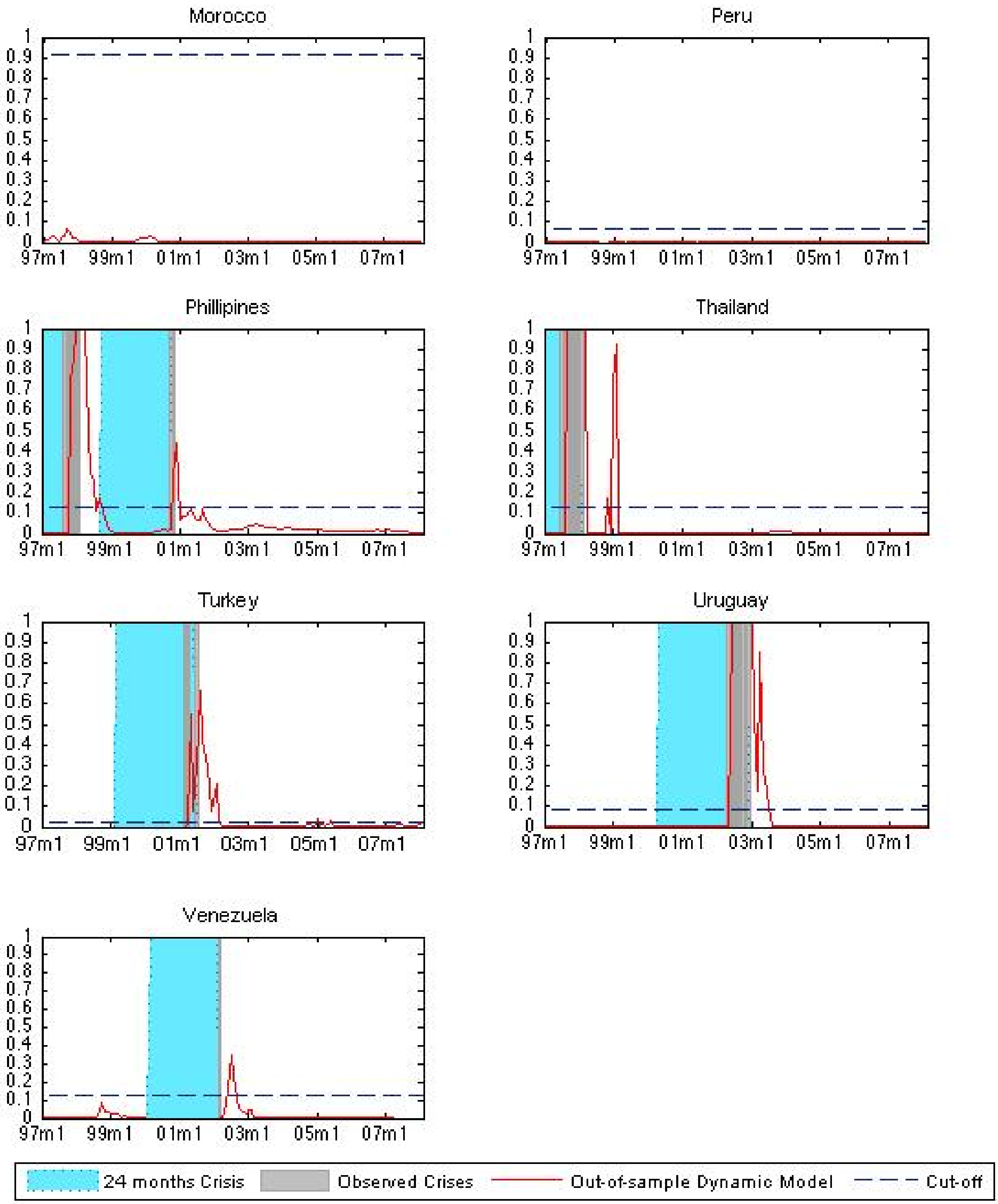

FIGURE 6 – Predicted probability of crisis (24-months-ahead forecasts) - out-of-sample (continued)

Table 1 – Estimation results of the time-series logit models

Country	Indicator	Coefficient Model 1	Model 2	Model 3	Model 4
Argentina	Intercept	-4.905*** (1.117)	-4.828*** (0.809)	-4.432*** (1.158)	-4.184*** (1.047)
	Lagged binary variable		2.527** (1.062)		2.384** (0.915)
	Growth of international reserves	-7.703** (3.783)	-5.398* (2.676)	-7.135*** (3.266)	-4.832** (2.255)
	Growth of M2 to reserves	-1.602 (1.051)	-1.156 (0.806)	-1.394 (0.955)	-0.880 (0.693)
	Lagged index			0.106 (0.107)	0.143 (0.135)
Brazil	Intercept	-3.293*** (0.481)	-3.579*** (0.423)	-0.621*** (0.167)	-0.808*** (0.246)
	Lagged binary variable		2.363*** (0.874)		0.655 (0.596)
	Growth of international reserves	-3.289 (1.997)	-2.433 (1.753)	-1.087*** (0.285)	-1.034*** (0.330)
	Growth of M2 to reserves	-0.047 (0.069)	-0.042 (0.057)	0.017*** (0.004)	0.018*** (0.004)
	Lagged index			0.835*** (0.039)	0.794*** (0.060)
Chile	Intercept	-4.413*** (0.747)	-4.405*** (0.758)	-2.104*** (0.812)	-0.984** (0.478)
	Lagged binary variable		-4.140*** (1.397)		1.613* (0.900)
	Growth of international reserves	-1.447 (3.754)	-1.395 (3.839)	-0.086 (0.312)	0.788*** (0.282)
	Growth of M2 to reserves	-3.029 (2.303)	-3.051 (2.359)	-0.993 (0.968)	0.090 (0.091)
	Lagged index			0.531*** (0.158)	0.809*** (0.098)
Indonesia	Intercept	-5.583*** (0.927)	-5.640*** (0.913)	-8.501*** (2.009)	-6.971*** (1.334)
	Lagged binary variable		3.961*** (1.454)		4.246** (1.886)
	Growth of international reserves	-2.738 (3.912)	-0.086 (3.967)	-5.183 (8.408)	-0.537 (5.706)
	Growth of M2 to reserves	-10.12*** (2.608)	-6.355*** (1.938)	-15.45*** (5.029)	-8.574*** (3.224)
	Lagged index			-0.481*** (0.083)	7-0.207 (0.169)
Israel	Intercept	-8.228*** (1.418)	-23.07** (11.063)	-9.323*** (2.382)	-37.22 (65.094)
	Lagged binary variable		-10.10 (6.360)		-20.65 (37.37)
	Growth of international reserves	-54.41*** (10.26)	-209.8* (112.3)	-59.41*** (10.89)	-374.2 (669.5)
	Growth of M2 to reserves	-22.64*** (4.615)	-89.33* (47.22)	-23.81*** (5.249)	-168.5 (304.3)
	Lagged index			-0.124 (0.155)	0.157** (0.079)

Note: The standard errors are reported in the parentheses. Significance at one percent level is denoted by ***, at five percent level by ** and at ten percent level by *.

Table 2 – Estimation results of the time-series logit models (continued)

		Coefficient			
Country	Indicator	Model 1	Model 2	Model 3	Model 4
South Korea	Intercept	-33.65***	-41.55***	-24.83	-303.6
		(5.959)	(7.351)	(68.57)	(25930)
	Lagged binary variable		76.76***		466.7
			(17.19)		(39249)
	Growth of international reserves	-265.9***	-266.6***	-314.2	-1033
		(48.85)	(40.94)	(1158)	(82816)
	Growth of M2 to reserves	-176.9***	-31.05***	-131.0	-178.4
		(31.83)	(9.330)	(385.3)	(20333)
	Lagged index			(0.511)	(-0.623)
				(0.397)	(11.96)
Malaysia	Intercept	-4.253***	-5.246***	-5.952***	-6.177***
		(0.760)	(1.039)	(1.144)	(1.197)
	Lagged binary variable		6.092***		6.596***
			(1.752)		(2.035)
	Growth of international reserves	-12.78***	-5.090	-17.21***	-6.822
		(2.759)	(4.138)	(4.967)	(5.363)
	Growth of M2 to reserves	-5.640***	-0.448	-8.381**	-1.656
		(1.723)	(1.895)	(3.447)	(1.985)
	Lagged index			-0.374**	-0.188***
				(0.150)	(0.071)
Mexico	Intercept	-3.188***	-4.343***	-4.290***	-5.200***
		(0.681)	(0.684)	(0.801)	(0.883)
	Lagged binary variable		5.927***		6.932***
			(1.893)		(2.639)
	Growth of international reserves	-5.135	-0.746	-6.857	-1.221
		(3.298)	(2.459)	(5.033)	(3.665)
	Growth of M2 to reserves	-2.543	1.173	-3.452	1.383
		(1.983)	(3.662)	(3.510)	(4.995)
	Lagged index			-0.329	-0.196***
				(0.242)	(0.066)
Morocco	Intercept	-6.812***	-6.809***	-1.899***	-1.530***
		(1.020)	(1.033)	(0.298)	(0.189)
	Lagged binary variable		-0.514		-2.588***
			(1.866)		(0.769)
	Growth of international reserves	-6.700***	-6.699***	-1.473**	-1.116**
		(1.422)	(1.421)	(0.687)	(0.506)
	Growth of M2 to reserves	-17.80***	-17.79***	-4.971***	-3.897***
		(2.960)	(2.960)	(1.687	(1.240)
	Lagged index			0.729***	0.777***
				(0.042)	(0.025)
Peru	Intercept	-5.151***	-5.939***	-2.787***	-6.793***
		(0.961)	(0.840)	(0.709)	(2.993)
	Lagged binary variable		3.264***		3.600***
			(0.999)		(1.341)
	Growth of international reserves	-13.23***	-11.77***	-7.706***	-13.44*
		(2.519)	(2.808)	(1.626)	(7.037)
	Growth of M2 to reserves	-0.476	-0.574	-0.439	-0.525
		(0.696)	(0.712)	(0.253)	(0.941)
	Lagged index			0.477***	-0.144
				(0.094)	(0.493)

Note: The standard errors are reported in the parentheses. Significance at one percent level is denoted by ***, at five percent level by ** and at ten percent level by *.

Table 3 – Estimation results of the time-series logit models (continued)

		Coefficient			
Country	Indicator	Model 1	Model 2	Model 3	Model 4
Philippines	Intercept	-3.300***	-3.754***	-5.178***	-5.647***
		(0.532)	(0.534)	(1.319)	1.590)
	Lagged binary variable		2.967***		2.832**
			(1.131)		(1.299)
	Growth of international reserves	-10.595***	-7.135**	-16.586***	-15.833**
		(3.192)	(3.261)	(5.407)	(6.510)
	Growth of M2 to reserves	-5.645***	-3.280**	-8.879***	-6.493***
		(1.427)	(1.296)	(2.702)	(2.470)
	Lagged index			-0.473***	-0.436
				(0.121)	(0.233)
Thailand	Intercept	-6.387***	-8.068***	-13.81	-12.30
		(1.545)	(2.776)	(32.12)	24.86)
	Lagged binary variable		5.497***		2.514***
			(1.496)		(1.205)
	Growth of international reserves	-40.56***	-35.99	-113.1	-87.37
		(11.65)	(20.73)	(266.6)	(208.7)
	Growth of M2 to reserves	5.873**	10.84**	37.13	29.79
		(2.790)	(4.866)	(90.47)	(70.38)
	Lagged index			0.579***	0.525***
				(0.043)	(0.180)
Turkey	Intercept	-5.721***	-5.556***	-10.21	-10.90
		(1.627)	(1.651)	(6.460)	(6.817)
	Lagged binary variable		0.767		2.253
			(1.609)		(1.507)
	Growth of international reserves	-15.11***	-13.43**	-29.89	-27.99
		(3.997)	(5.899)	(22.26)	(24.67)
	Growth of M2 to reserves	-4.562**	-4.241*	-7.292	-7.443
		(2.045)	(2.545)	(4.589)	(6.055)
	Lagged index			-0.502***	-0.617***
				(0.095)	(0.166)
Uruguay	Intercept	-4.717***	-5.053***	-7.485***	-4.464***
		(0.693)	(0.634)	(2.309)	(0.931)
	Lagged binary variable		2.971***		2.923***
			(1.046)		(0.926)
	Growth of international reserves	-10.17***	-7.704***	-15.731***	-6.640***
		(2.638)	(1.776)	(4.845)	(2.196)
	Growth of M2 to reserves	-2.336	-2.803	7-3.053	-3.017**
		(2.404)	(1.735)	(2.947)	(1.521)
	Lagged index			-0.537**	0.136
				(0.246)	(0.159)
Venezuela	Intercept	-6.088***	-5.914***	-1.427***	-5.304***
		(1.111)	(1.196)	(0.389)	(1.309)
	Lagged binary variable		3.470**		3.370***
			(1.432)		(1.210)
	Growth of international reserves	-15.48***	-11.72***	-4.779***	-10.33***
		(4.092)	(4.059)	(1.233)	(3.884)
	Growth of M2 to reserves	-2.164**	-0.235	0.359***	0.017
		(0.940)	(1.314)	(0.115)	(1.338)
	Lagged index			0.804***	0.103
				(0.037)	(0.207)

Note:The standard errors are reported in the parentheses. Significance at one percent level is denoted by ***, at five percent level by ** and at ten percent level by *.

Table 4 – SBC information criterion for the time-series logit models

Country	Model 1	Model 2	Model 3	Model 4
	SBC	SBC	SBC	SBC
Argentina	57.62	**57.47**	63.07	62.72
Brazil	88.39	87.72	**87.20**	91.94
Chile	**49.03**	54.53	54.81	58.68
Indonesia	54.90	**49.80**	58.70	55.05
Israel	**26.42**	30.49	31.88	35.14
South Korea	**16.75**	22.33	22.33	31.44
Malaysia	50.16	**40.35**	54.51	45.66
Mexico	101.1	**67.70**	105.4	72.29
Marocco	**27.86**	33.43	33.60	39.15
Peru	62.50	**53.73**	66.37	59.22
Philippines	75.14	**70.75**	76.82	75.00
Thailand	33.21	32.47	**30.43**	35.30
Turkey	**44.78**	50.04	45.13	48.86
Uruguay	62.06	**58.89**	66.65	64.35
Venezuela	74.60	**68.01**	82.78	73.48

Note: Bold values correspond to the best model according to SBC.

Table 5 – Estimation results of the panel logit models

Indicator	Coefficients		
	All countries	Poolable countries (cluster1)	Poolable countries (cluster2)
Lagged binary variable	4.383***	4.294***	3.608***
	(0.304)	(0.332)	(0.955)
Growth of international reserves	-4.092***	-3.614***	-7.496***
	(0.665)	(0.681)	(2.695)
Growth of M2 to reserves	-0.542*	-0.550*	-0.459
	0.298	(0.325)	(0.776)
Fixed effects			
Argentina	-5.083	-4.919	−−
Brazil	-4.076	-4.004	−−
Chile	-4.660	-4.657	−−
Indonesia	-4.066	-4.030	−−
Israel	-5.308	−−	−−
South Korea	-4.218	−−	−−
Malaysia	-4.436	-4.375	−−
Mexico	-4.102	-4.021	−−
Marocco	-5.347	−−	-5.170
Peru	-4.339	−−	-4.825
Philippines	-4.096	-4.033	−−
Thailand	-4.334	-4.279	−−
Turkey	-4.523	-4.441	−−
Uruguay	-4.682	-4.552	−−
Venezuela	-4.577	-4.450	−−

Note: The standard errors are reported in the parentheses. Significance at one percent level is denoted by ***, at five percent level by ** and at ten percent level by *.

Table 6 – Optimal cut-off identification for time-series models

	Static logit			Dynamic logit			Dynamic Markov switching		
	Cut-off	Sensitivity	Specificity	Cut-off	Sensitivity	Specificity	Cut-off	Sensitivity	Specificity
Argentina	0.011	1.000	0.767	0.010	1.000	0.767	0.672	0.857	0.857
Brazil	0.064	0.500	0.859	0.042	0.700	0.847	0.026	0.900	0.694
Chile	0.014	0.667	0.714	0.014	0.667	0.721	< 0.001	1.000	< 0.001
Indonesia	0.061	1.000	0.917	0.036	0.909	0.969	0.908	0.818	0.992
Israel	0.066	1.000	0.992	0.203	1.000	0.992	0.998	0.500	0.973
South Korea	0.005	1.000	1.000	0.606	1.000	1.000	0.999	1.000	0.938
Malaysia	0.033	1.000	0.938	0.008	1.000	0.860	0.823	1.000	0.895
Mexico	0.244	0.643	0.972	0.034	0.857	0.988	0.567	1.000	0.873
Marocco	0.010	1.000	0.883	0.010	1.000	0.883	0.000	1.000	0.000
Peru	0.112	1.000	0.944	0.069	1.000	0.956	0.998	0.077	0.960
Philippines	0.038	1.000	0.784	0.022	1.000	0.733	0.987	1.000	0.882
Thailand	0.183	1.000	0.984	0.174	1.000	0.996	0.999	0.875	0.887
Turkey	0.071	0.889	0.957	0.107	0.889	0.969	0.897	1.000	0.957
Uruguay	0.031	1.000	0.851	0.021	1.000	0.843	0.937	1.000	0.984
Venezuela	0.065	0.929	0.892	0.092	0.929	0.948	0.999	1.000	0.725

Note: For each country we identify the optimal cut-off by using the accuracy measures method, so as to give more weight to the correct identification of crisis periods (sensitivity).

Table 7 – Evaluation criteria for the time-series logit models

Static time-series logit model						
Country	AUC	Kuiper score	Pietra index	Bayesian error rate	QPS	LPS
Argentina	0.938	0.767	0.271	0.026	0.043	10.07
Brazil	0.710	0.359	0.127	0.030	0.069	0.145
Chile	0.606	0.380	0.134	0.011	0.022	0.061
Indonesia	0.979	0.917	0.324	0.026	0.044	0.072
Israel	0.994	0.992	0.351	0.008	0.011	0.018
South Korea	1.000	1.000	0.354	0.000	0.000	0.000
Malaysia	0.978	0.938	0.332	0.023	0.039	0.063
Mexico	0.784	0.615	0.217	0.030	0.073	0.161
Marocco	0.888	0.883	0.312	0.004	0.008	0.021
Peru	0.974	0.944	0.334	0.030	0.059	0.086
Philippines	0.915	0.784	0.277	0.034	0.062	0.110
Thailand	0.995	0.984	0.348	0.011	0.021	0.031
Turkey	0.976	0.846	0.299	0.015	0.026	0.053
Uruguay	0.959	0.851	0.301	0.026	0.051	0.086
Venezuela	0.955	0.821	0.290	0.038	0.066	0.109
Dynamic time-series logit model						
Country	AUC	Kuiper score	Pietra index	Bayesian error rate	QPS	LPS
Argentina	0.946	0.767	0.271	0.019	0.033	0.066
Brazil	0.799	0.547	0.193	0.034	0.068	0.135
Chile	0.601	0.388	0.137	0.011	0.022	0.061
Indonesia	0.981	0.878	0.310	0.011	0.024	0.052
Israel	0.994	0.992	0.351	0.008	0.011	0.015
South Korea	1.000	1.000	0.354	0.000	0.003	0.004
Malaysia	0.978	0.860	0.304	0.008	0.015	0.034
Mexico	0.880	0.845	0.299	0.019	0.038	0.086
Marocco	0.888	0.883	0.312	0.004	0.008	0.021
Peru	0.989	0.956	0.338	0.023	0.038	0.059
Philippines	0.935	0.733	0.259	0.026	0.049	0.092
Thailand	0.998	0.996	0.352	0.004	0.011	0.019
Turkey	0.978	0.858	0.303	0.015	0.027	0.052
Uruguay	0.966	0.843	0.298	0.015	0.034	0.069
Venezuela	0.961	0.877	0.310	0.023	0.046	0.086

Note: The AUC criteria takes values between 0.5 and 1, 1 being the perfect model. Kuiper's score should have positive values if the model identifies well the crisis periods. Pietra index takes values from -0.354 to 0.354, the higher its level, the better the model. Bayesian error rate takes values between 0 and 1, 0 corresponding to the perfect model. QPS ranges from 0 to 2, 0 being perfect accuracy, while LPS ranges from 0 to ∞, 0 being perfect accuracy.

Table 8 – Evaluation criteria for the dynamic Markov-switching model

Country	AUC	Kuiper score	Pietra index	Bayesian error rate	QPS	LPS
Argentina	0.871	0.714	0.252	0.026	0.754	1.711
Brazil	0.783	0.594	0.210	0.038	0.502	3.807
Chile	0.010	0.000	0.000	0.011	1.198	3.661
Indonesia	0.817	0.810	0.286	0.015	1.199	1.602
Israel	0.536	0.473	0.167	0.008	0.480	1.079
South Korea	0.969	0.938	0.332	0.023	0.171	1.081
Malaysia	0.955	0.895	0.317	0.026	0.239	1.526
Mexico	0.971	0.873	0.308	0.023	0.598	0.903
Marocco	0.028	0.000	0.000	0.004	0.436	1.087
Peru	0.268	0.037	0.013	0.049	1.121	1.950
Philippines	0.948	0.882	0.312	0.038	0.526	1.399
Thailand	0.828	0.762	0.269	0.030	1.203	3.108
Turkey	0.992	0.957	0.338	0.011	0.386	0.608
Uruguay	0.995	0.984	0.348	0.011	0.546	0.814
Venezuela	0.863	0.725	0.256	0.053	0.997	5.528

Note: The AUC criteria takes values between 0.5 and 1, 1 being the perfect model. Kuiper's score should have positive values if the model identifies well the crisis periods. Pietra index takes values from -0.354 to 0.354, the higher its level, the better the model. Bayesian error rate takes values between 0 and 1, 0 corresponding to the perfect model. QPS ranges from 0 to 2, 0 being perfect accuracy, while LPS ranges from 0 to ∞, 0 being perfect accuracy.

Table 9 – Comparison tests

	Static vs. dynamic[a] (Clark-West test)		Dynamic logit vs. Markov[b] (Diebold Mariano test)		Dynamic panel logit vs. Markov[c] (Diebold Mariano test)	
Country	test statistic	p-value	test statistic	p-value	test statistic	p-value
Argentina	2.144	**0.016**	25.54	$<$ **0.001**	25.61	$<$ **0.001**
Brazil	1.136	0.128	8.004	$<$ **0.001**	7.830	$<$ **0.001**
Chile	1.036	0.150	21.89	$<$ **0.001**	21.71	$<$ **0.001**
Indonesia	2.526	**0.006**	21.89	$<$ **0.001**	48.04	$<$ **0.001**
Israel	0.434	0.332	10.04	$<$ **0.001**	−−	$<$ **0.001**
South Korea	1.037	0.150	5.157	$<$ **0.001**	−−	$<$ **0.001**
Malaysia	2.656	**0.004**	5.985	$<$ **0.001**	5.885	$<$ **0.001**
Mexico	3.291	$<$ **0.001**	29.02	$<$ **0.001**	25.81	$<$ **0.001**
Marocco	0.668	0.252	9.726	$<$ **0.001**	8.701	$<$ **0.001**
Peru	2.776	**0.003**	40.70	$<$ **0.001**	22.39	$<$ **0.001**
Philippines	2.358	**0.009**	9.094	$<$ **0.001**	6.976	$<$ **0.001**
Thailand	2.067	**0.019**	21.77	$<$ **0.001**	18.12	$<$ **0.001**
Turkey	2.067	**0.019**	11.10	$<$ **0.001**	6.048	$<$ **0.001**
Uruguay	2.827	**0.002**	14.33	$<$ **0.001**	10.89	$<$ **0.001**
Venezuela	2.977	$<$ **0.001**	16.40	$<$ **0.001**	11.98	$<$ **0.001**

a - Static vs. dynamic time series logit model.

b - Dynamic time-series logit model vs. Markov switching.

c - Dynamic panel logit model (poolable countries) vs. Markov switching.

Note: The null hypothesis of both tests is the equality of predictive performance of the two models. The alternative of the Clark-West test indicates that the non-constraint model (the bigger one) is better than the other one. Under the null hypothesis, the MSPE-adj statistic follows a normal distribution with a critical unilateral value of 1.645(5%). The alternative of the Diebold Mariano test indicates that the first model is better than the other one. Under the null hypothesis, the test statistic follows a normal distribution. Bold entries indicate significance at the 5% level.

Table 10 – Optimal cut-off identification for dynamic panel logit models

	All countries			Poolable countries		
	Cut-off	Sensitivity	Specificity	Cut-off	Sensitivity	Specificity
Argentina	0.025	0.857	0.942	0.023	0.857	0.930
Brazil	0.043	0.700	0.894	0.043	0.700	0.898
Chile	0.015	0.333	0.973	0.014	0.333	0.966
Indonesia	0.046	0.909	0.984	0.043	0.909	0.984
Israel	0.008	1.000	0.962	−−	−−	−−
South Korea	0.027	1.000	0.996	−−	−−	−−
Malaysia	0.016	1.000	0.860	0.033	0.857	0.996
Mexico	0.074	0.929	0.964	0.068	0.929	0.968
Marocco	0.001	1.000	0.174	0.020	0.900	0.769
Peru	0.030	1.000	0.952	0.019	1.000	0.977
Philippines	0.019	0.900	0.757	0.025	0.889	0.973
Thailand	0.019	1.000	0.977	0.015	1.000	0.851
Turkey	0.025	0.889	0.973	0.021	1.000	0.813
Uruguay	0.013	1.000	0.835	0.000	1.000	0.000
Venezuela	0.025	0.929	0.888	0.061	1.000	0.956

Note: For each country we identify the optimal cut-off by using the accuracy measures method, so as to give more weight to the correct identification of crisis periods (sensitivity). Cut-off values are in bold.

Table 11 – Evaluation criteria for the dynamic panel logit model

All countries						
Country	AUC	Kuiper score	Pietra index	Bayesian error rate	QPS	LPS
Argentina	0.950	0.799	0.282	0.019	0.036	0.071
Brazil	0.806	0.594	0.210	0.038	0.082	0.155
Chile	0.475	0.307	0.108	0.011	0.026	0.069
Indonesia	0.913	0.893	0.316	0.015	0.032	0.070
Israel	0.983	0.962	0.340	0.008	0.011	0.027
South Korea	0.999	0.996	0.352	0.004	0.013	0.032
Malaysia	0.978	0.860	0.304	0.008	0.017	0.038
Mexico	0.924	0.893	0.316	0.023	0.044	0.097
Marocco	0.271	0.174	0.062	0.004	0.008	0.028
Peru	0.988	0.952	0.337	0.023	0.039	0.071
Philippines	0.905	0.657	0.232	0.030	0.048	0.096
Thailand	0.994	0.977	0.345	0.008	0.016	0.036
Turkey	0.976	0.862	0.305	0.015	0.035	0.069
Uruguay	0.964	0.835	0.295	0.015	0.035	0.073
Venezuela	0.964	0.817	0.289	0.023	0.049	0.095
Poolable countries						
Country	AUC	Kuiper score	Pietra index	Bayesian error rate	QPS	LPS
Argentina	0.950	0.787	0.278	0.019	0.036	0.071
Brazil	0.810	0.598	0.211	0.038	0.081	0.153
Chile	0.443	0.299	0.106	0.011	0.025	0.069
Indonesia	0.913	0.893	0.316	0.015	0.032	0.069
Israel	−−	−−	−−	−−	−−	−−
South Korea	−−	−−	−−	−−	−−	−−
Malaysia	0.977	0.853	0.302	0.008	0.017	0.039
Mexico	0.923	0.897	0.317	0.023	0.044	0.095
Marocco	0.910	0.669	0.236	0.030	0.048	0.096
Peru	0.994	0.977	0.345	0.008	0.016	0.037
Philippines	0.977	0.862	0.305	0.015	0.035	0.070
Thailand	0.965	0.851	0.301	0.015	0.035	0.073
Turkey	0.965	0.813	0.287	0.023	0.049	0.096
Uruguay	0.167	0.000	0.000	0.004	0.008	0.032
Venezuela	0.989	0.956	0.338	0.023	0.037	0.062

Note: The AUC criteria takes values between 0.5 and 1, 1 being the perfect model. Kuiper's score should have positive values if the model identifies well the crisis periods. Pietra index takes values from -0.354 to 0.354, the higher its level, the better the model. Bayesian error rate takes values between 0 and 1, 0 corresponding to the perfect model. QPS ranges from 0 to 2, 0 being perfect accuracy, while LPS ranges from 0 to ∞, 0 being perfect accuracy. For Malaysia and Morocco time-series analyses have been performed the results being available in table 11.

Table 12 – Comparison test of dynamic time-series and panel logit models

	Time series vs Panel - All countries		Time series vs Panel - Poolable countries	
Country	test statistic	p-value	test statistic	p-value
Argentina	0.715	0.474	0.662	0.508
Brazil	1.496	0.135	1.491	0.136
Chile	1.343	0.179	1.391	0.164
Indonesia	1.402	0.161	1.431	0.152
Israel	0.139	0.889	−−	−−
South Korea	1.304	0.192	−−	−−
Malaysia	0.782	0.434	0.803	0.422
Mexico	0.834	0.404	0.801	0.423
Marocco	1.033	0.302	2.320	**0.020**
Peru	0.138	0.890	-1.446	0.148
Philippines	-0.059	0.953	-0.651	0.515
Thailand	0.863	0.388	1.541	0.123
Turkey	-0.832	0.406	1.075	0.282
Uruguay	0.160	0.873	-1.746	0.081
Venezuela	0.755	0.450	-2.308	**0.021**

Note: The null hypothesis of the Diebold Mariano test is the equality of predictive performance of the two models. The alternative indicates that the first model is better than the other one. Under the null hypothesis, the test statistic follows a normal distribution. Bold entries indicate significance at the 5% level.

Table 13 – Optimal cut-off identification (Out-of-sample exercise)

	Cut-off	Sensitivity	Specificity
One-month-ahead forecasts			
Argentina	0.011	0.8	0.938
Brazil	0.11	0	0.992
Chile	0.021	0	0.812
Philippines	0.065	0.625	0.857
Uruguay	0.028	0.875	0.944
Venezuela	0.162	0	0.977
24-months-ahead forecasts			
Argentina	0.001	0.964	0.434
Brazil	0.026	0.958	0.809
Chile	0.170	1.000	0.991
Indonesia	0.664	1.000	0.983
South Korea	0.032	1.000	0.949
Malaysia	0.040	1.000	0.992
Philippines	0.126	0.974	0.969
Thailand	0.130	1.000	0.967
Turkey	0.020	0.964	0.840
Uruguay	0.083	0.968	0.971
Venezuela	0.131	0.958	0.945

Note: For each country we identify the optimal cut-off by using the accuracy measures method, so as to give more weight to the correct identification of crisis periods (sensitivity). The values of the cut-off are calculated on the basis of the in-sample dataset (January 1986 - December 1996). The other countries, *i.e.* Israel, South Korea, Malaysia, Mexico, Morocco, Peru, Thailand and turkey do not register any in sample or out-of-sample crises.

Table 14 – Evaluation criteria for the out-of-sample dynamic logit model

Country	AUC	Kuiper score	Pietra index	Bayesian error rate	QPS	LPS
One-month-ahead forecasts						
Argentina	0.874	0.738	0.280	0.015	0.054	0.260
Brazil	0.737	-0.008	0.261	0.007	0.023	0.055
Chile	0.545	-0.188	0.183	0.007	0.018	0.062
Philippines	0.690	0.482	0.207	0.045	0.094	2.914
Uruguay	0.915	0.819	0.307	0.015	0.047	0.244
Venezuela	0.372	-0.023	0.000	0.007	0.019	5.135
24-months-ahead forecasts						
Argentina	0.947	0.398	0.325	0.022	0.045	1.504
Brazil	0.985	0.767	0.336	0.015	0.032	0.081
Chile	0.992	0.991	0.350	0.007	0.015	0.076
Indonesia	0.993	0.983	0.351	0.007	0.024	0.172
South Korea	0.996	0.949	0.351	0.007	0.015	0.147
Malaysia	0.996	0.992	0.351	0.007	0.015	0.087
Philippines	0.973	0.942	0.341	0.015	0.043	0.126
Thailand	0.994	0.967	0.345	0.015	0.049	0.131
Turkey	0.971	0.804	0.338	0.015	0.030	0.081
Uruguay	0.966	0.939	0.339	0.015	0.030	3.115
Venezuela	0.957	0.904	0.336	0.015	0.037	0.187

Note: The AUC criteria takes values between 0.5 and 1, 1 being the perfect model. Kuiper's score should have positive values if the model identifies well the crisis periods. Pietra index takes values from -0.354 to 0.354, the higher its level, the better the model. Bayesian error rate takes values between 0 and 1, 0 corresponding to the perfect model. QPS ranges from 0 to 2, 0 being perfect accuracy, while LPS ranges from 0 to ∞, 0 being perfect accuracy.